

Using Big Data Analytics to facilitate Management Control Systems in the Agri-food and beverage industry: A Strong Structuration Approach

by

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Abstract

This study examines the role of Big Data Analytics (BDA) in supporting Management Control Systems (MCS) within the Irish agri-food and beverage sector. Using qualitative data gathered through semi-structured interviews with financial controllers, management accountants, and IT managers, the study investigates how BDA is implemented to improve organisational control and decision-making. The analysis is grounded in Strong Structuration Theory (SST), offering a detailed perspective on the dynamic relationship between technological capabilities and organisational structures. The findings highlight the transformative potential of BDA in fostering more responsive and strategically aligned MCS.

Theoretically, this study emphasises the importance of organisations developing the ability to extract information from diverse data sources to support decision-making and other organisational functions. It offers specific insights into factors that influence the effective use of BDA to ensure a robust MCS, which have not been previously documented in the literature, thus making a significant contribution. BDA helps organisations stay aligned with their strategies, thereby increasing the chances of achieving their primary goals. It highlights that both external factors (such as regulations and market demands) and internal structures (like organisational strategies and employee capabilities) influence the effective integration of BDA into MCS. Using SST, the research provides a framework to analyse how managers, technologies, and organisational contexts interact to shape outcomes.

Practical contributions emphasise recommendations that show how the challenges of implementing MCS can be mitigated by using BDA technologies. Practically, the study shows that BDA improves traceability, compliance, and sustainability while enabling more accurate forecasting and real-time decision-making. Ultimately, it emphasises the importance of strong communication between IT and operational teams to fully realise the benefits of data-driven management control. The study illustrates how BDA helps monitor productivity, optimise resource allocation, and reduce waste throughout the value chain. While there are limitations to the study, the research provides strong theoretical and practical contributions and lays a clear foundation for a stream of research on how BDA affects MCS, and how MCS affects the use and operationalisation of BDA.

Declaration

I hereby certify that this material, which I now submit for assessment on the programme leading to the award of a Doctor of Philosophy, is entirely my own work. I have exercised reasonable care to ensure that the work is original, does not, to the best of my knowledge, breach any copyright law, and has not been taken from the work of others except where such work has been cited and acknowledged within the text.

Signed: C Mongwe (Candidate) ID No.: 10250575 Date: 30/10/2025

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Table of Contents

Chapter 1 Introduction	1
1.1 Introduction	1
1.2 Background to this study	1
1.3 Rationale for this study	2
1.4 Research Question and Research Approach	3
1.5 Conceptual framework	5
1.6 Thesis Structure	6
Chapter 2 Management Control Systems	8
2.1 Introduction	8
2.2 Definition and Evolution of Management Control Systems.....	9
2.3 The paradigms that govern MCS	11
2.3.1 Belief Systems	14
2.3.2 Boundary Systems	15
2.3.3 Diagnostic Control Systems.....	16
2.3.4 Interactive Control Systems.....	17
2.3.5 LOC – Benefits of combining the LOCs.....	18
2.4 MCS and strategy	19
2.5 Approaches to MCS design and implementation.....	23
2.6 Application of MCS.....	25
2.6.1 Performance Measurement	25
2.6.2 Contingency Theory Approach to MCS Implementation	25
2.7 Possible Challenges to MCS.....	27
2.8 Conclusion	28
Chapter 3 Big Data Analytics	29
3.1 Introduction	29
3.2 Definition and evolution of big data	30
3.3 Types of Analytics	33
3.3.1 Descriptive Analytics.....	34
3.3.2 Diagnostic Analytics	35
3.3.3 Predictive Analytics.....	35

3.3.4 Prescriptive Analytics	36
3.3.5 Advanced and emerging types of analytics	37
3.3.6 Section Summary	38
3.4 Common BDA themes:	39
3.4.1 Application of BDA in Decision-making.....	40
3.4.2 BDA Techniques and Value Creation.....	41
3.4.3 Barriers to the strategic application of BDA in MCS implementation	42
3.5 Conclusion.....	47
Chapter 4 Research Framework—Strong Structuration Theory (SST)	49
4.1 Introduction	49
4.2 Relevance of Strong Structuration Theory in Research.....	49
4.3 Strong Structuration Theory as a Theoretical Framework for Studying the BDA-MCS Relationship.....	55
4.3.1 Rationale for using SST as an analytical framework	57
4.3.2 Strong Structuration Theory: Methodological Bracketing	59
4.3.2.1 Bracketing External Structures (Agent’s context analysis):.....	61
4.3.2.2 Bracketing Internal Structures (Agent’s conduct analysis):	63
4.3.2.3 Active agency:	66
4.3.2.4 Outcomes.....	69
4.4 Chapter Summary	70
Chapter 5 Methodology	71
5.1 Introduction	71
5.2 The Research Question and Objectives	71
5.3 Research Methodological Approach.....	73
5.3.1 Research Philosophy and Paradigms	73
5.3.2 Approach to Theory Development.....	76
5.3.3 Methodological Choice.....	78
5.3.4 Research Strategy	80
5.4 Data Collection: Techniques and Procedures	82
5.4.1 Case Study Approach.....	83
5.4.2 Strategies for Selecting Cases.....	84
5.4.3 Case Study Profiles.....	86
5.4.4 Semi-structured Interviews	92
5.4.5 Data Triangulation	96
5.4.6 Quality and Rigour Assurance	97

5.5 Data Analysis	101
5.5.1 Data Analysis: Techniques and Procedures.....	102
5.5.2 Analytical Process: Phases and Steps	103
5.5.2.1 Phase 1: Familiarisation.....	111
5.5.2.2 Phase 2: Generating initial codes (Open coding).....	113
5.5.2.3 Phase 3: Searching for themes (Axial coding).....	116
5.5.2.4 Phase 4: Reviewing Themes (Developing themes)	118
5.5.2.5 Phase 5: Refining and naming themes (Developing themes)	119
5.5.2.6 Phase 6: Creating the report.....	119
5.6 Chapter Summary	120
Chapter 6 Findings.....	121
6.1 Introduction	121
6.2 Outcomes as a result of structures	122
6.3 Themes.....	124
6.3.1 Sustainability (T1)	126
6.3.2 Innovation (T2).....	137
6.3.3 Product Costing (T3)	142
6.3.4 Quality assurance (T4).....	154
6.3.5 Performance measurement and management (T5).....	159
6.3.6 Challenges (T6).....	168
6.4 Summary of Key Findings.....	177
Chapter 7 Discussion	181
7.1 Introduction	181
7.2 Interpreting External Pressures with BDA-enabled Controls	181
7.2.1 Introduction.....	181
7.2.2 Resource Efficiency	183
7.2.3 Regulatory Compliance	192
7.2.4 Process Automation	195
7.2.5 Supply Chain Management.....	198
7.3 Contextualising the use of BDA to Facilitate MCS: Using SST to structure the alliance between BDA and MCS	201
7.3.1 Introduction.....	201

7.3.2 Human agency and organisational systems in agri-food and beverage	203
manufacturing: Navigating duality of structure	203
7.3.3 The Anatomy of Food Manufacturing: How Internal Structure Shapes Outcomes	205
7.3.4 Reinforcement and Transforming Food Manufacturing: Expected Outcomes from SST Analysis.....	211
7.4 Revisiting prior literature on the use of BDA in MCS	218
7.4.1. Introduction.....	218
7.4.2 BDA and MCS relationship – A reflection on literature	219
Chapter 8 Contributions and Recommendations	220
8.1 Introduction	220
8.2 Theoretical contributions.....	222
8.3 Practical Contributions.....	226
8.4 Limitations of the Research	229
8.5 Recommendations for Future Research	233
8.6 Concluding Remarks	237
Bibliography	239
Appendices	285
Appendix A – Ethical Approval	285
Appendix B– Participant’s Information Sheet	285
Appendix C – Consent Form for Participants	288
Appendix D – Interview Guide	290
Appendix E – Interview Questions	291
Appendix F – SST intersection with MCS themes	294
Appendix G – NVivo extracts (Themes)	294
Appendix H - Mapping of MCS and BDA themes to potential research areas based on MCS themes.....	298

List of Figures

FIGURE 1: THESIS ROADMAP (SOURCE: AUTHOR)	6
FIGURE 2: CONTROLLING BUSINESS STRATEGY: KEY VARIABLES THAT IMPACT BUSINESS STRATEGIES [SOURCE: SIMONS, 1995: 7]	13
FIGURE 3: A PROCESS MODEL OF THE RELATIONSHIP BETWEEN BUSINESS STRATEGY AND CONTROL [SOURCE: (SIMONS, 1991 P. 50)]	22
FIGURE 4: INTERACTIVE CONTROL STIMULATES INFORMATION SHARING AND NEW STRATEGIES [SOURCE: (SIMONS, 1995: 103)]	23
FIGURE 5 THE BDA CYCLE [ADAPTED FROM VITT ET AL. (2002)]	30
FIGURE 6: COMPILED FROM VARIOUS SOURCES (SOURCE: AUTHOR)	32
FIGURE 7: TYPES OF BUSINESS ANALYTICS – BUILT FROM VARIOUS SOURCES (SOURCE: AUTHOR).....	34
FIGURE 8: THE QUADRIPARTITE NATURE OF STRUCTURATION [SOURCE: ADAPTED FROM STONES (2005: 85)]	52
FIGURE 9: REVERSE FUNNEL APPROACH TO DATA ANALYSIS USING SST [ADAPTED FROM STONES (2015)]	60
FIGURE 10: SETTING UP PARTICIPANTS’ PROFILES (SOURCE: NVIVO DATA FILE)	111
FIGURE 11: NVIVO CASE NODE [SOURCE: NVIVO EXTRACT]	111
FIGURE 12: EXAMPLE OF DATA EXTRACT AND CODE (SOURCE: INTERVIEW TRANSCRIPT)	112
FIGURE 13: EXAMPLE OF ANNOTATION ON A CODE SNIPPET (SOURCE: NVIVO EXTRACT).....	115
FIGURE 14: DEVELOPING CATEGORIES - AXIAL CODING (SOURCE: NVIVO EXTRACT)	116
FIGURE 15: SEARCHING FOR THEMES - DEVELOPING THEMES (SOURCE: NVIVO EXTRACT)	117
FIGURE 16: REFINING AND NAMING THEMES - DEVELOPING THEMES [SOURCE: NVIVO EXTRACT]	118
FIGURE 17: INTERPLAY BETWEEN BDA, AGENCY AND OUTCOMES (SOURCE: AUTHOR)	121
FIGURE 18: EMERGING THEMES	124
FIGURE 19: PRODUCT LIFE CYCLE GRAPH [ADAPTED FROM DRURY 2018]	152
FIGURE 20: SUMMARY OF KEY FINDINGS	178
FIGURE 21: POTENTIAL USE OF BDA TO FACILITATE RESOURCE EFFICIENCY [SOURCE: AUTHOR]	184
FIGURE 22: POTENTIAL USE OF BDA TO FACILITATE REGULATORY COMPLIANCE [SOURCE: AUTHOR]	191
FIGURE 23: POTENTIAL USE OF BDA TO FACILITATE PROCESS AUTOMATION [SOURCE: AUTHOR]	194
FIGURE 24: POTENTIAL USE OF BDA TO FACILITATE SUPPLY CHAIN MANAGEMENT [SOURCE: AUTHOR]	198
FIGURE 25: THE FRAMEWORK FOR INDUSTRY COMPETITIVENESS	220

List of Tables

TABLE 1: THE ESSENCE OF STRATEGIC MANAGEMENT [SOURCE: LYNCH (2015: 8)]	20
TABLE 2: PARTICIPATING CASE COMPANIES' PROFILES.....	90
TABLE 3: PHASES OF THEMATIC ANALYSIS[ADAPTED FROM (BONELLO AND MEEHAN, 2019; BRAUN AND CLARKE, 2006)]	107
TABLE 4: CODES AND DESCRIPTION - INITIAL CODING PROCESS(SOURCE: NVIVO CODE EXTRACT) ..	113

Glossary of Abbreviations

MCS:	Management control systems
BDA:	Big data analytics
ICT:	Information and communication technologies
MSG:	Monosodium glutamate
IQF:	Individual Quick Freezing (commonly used in bakeries)
UTZ:	(“good” in Maya language), formerly called UTZ Certified, is a program and a label for sustainable farming
RSPO:	Roundtable for Sustainable Palm Oil
EMS:	Environmental Management System
CSR:	Corporate Social Responsibility
ERP:	Enterprise Resource Planning
SMEs:	Small and Medium-sized Enterprises
SBT:	Science-Based Targets
BRCGS:	Brand Reputation through Compliance Global Standard (initially stood for British Retail Consortium Global Standard)
PIF:	Pet Industry Federation
CEO:	Chief Executive Officer

Chapter 1 Introduction

1.1 Introduction

This study explores the contextual factors that shape the implementation of Big Data Analytics (BDA) enabled Management Control Systems (MCS) in the agri-food and beverage industry. To establish the foundation for this research, Section 1.2 presents the study's background. Section 1.3 then articulates the rationale underpinning the investigation, which is further elaborated in Section 1.4 through the formulation of the central research question and the corresponding objectives designed to address it. Section 1.5 provides a concise overview of the conceptual framework guiding this study. Lastly, Section 1.6 outlines the structure of the subsequent chapters comprising this thesis.

1.2 Background to this study

The rate at which data is generated from the food manufacturing process is growing in both depth and breadth. This rapid pace of growth is alarming for industry professionals (Ortner, 2025; Raza, 2025) and may significantly impact the modus operandi of MCS in this industry. This growth in data has given birth to the concept of big data, prompting the need for technologies to analyse and generate information from this diverse data (Chen, Chiang and Storey, 2012; Moffitt and Vasarhelyi, 2013; Bhimani and Willcocks, 2014; Warren, Moffitt and Byrnes, 2015). Therefore, BDA is an emerging technology that will take businesses time to understand. The importance of BDA in the agri-food and beverage industry also stems from the need for MCS strategies to keep pace with rapid information and communication technologies (ICT) changes. This trend is reflected in the evolution from Industry 4.0 to 5.0, incorporating a human-centric approach (Raja Santhi and Muthuswamy, 2023; Dacre *et al.*, 2024; Hassoun *et al.*, 2024; Maljugić *et al.*, 2024; Yang, Liu and Morgan, 2024; Vanitha, 2025).

Since MCS often depends on organisational strategies, and no two organisations will have the same strategies (Porter, 1996; Mintzberg, Ahlstrand and Lampel, 1998), the correct use of BDA to facilitate MCS cannot be overemphasised. MCS within the food manufacturing industry is more complex due to the industry's quest for operational efficiencies to ensure food safety and traceability, imposed by regulatory bodies and

customers (Vriezen, Plishka and Cranfield, 2023; Food Safety Authority of Ireland, 2024; Tran *et al.*, 2024).

1.3 Rationale for this study

Food and beverage manufacturing is a vital sector in contemporary economies, where organisations are increasingly required to uphold food safety standards through the use of traceability systems (Food Safety Authority of Ireland, 2024). These systems have garnered positive reception from consumers, reflecting growing public demand for transparency and accountability in food production (Tran *et al.*, 2024; Vriezen *et al.*, 2023). Systems initially developed to meet regulatory compliance requirements are now being reconceptualised as strategic tools for managerial decision-making and performance enhancement. Given the extensive data generated by such systems, management accountants are increasingly leveraging BDA to extract meaningful insights that inform and strengthen MCS.

ICT is supposed to facilitate these processes by providing the correct information promptly and efficiently (Davenport, 1998; Kanellou and Spathis, 2013; Seddon *et al.*, 2017). ICT systems, like other business assets, must be fit for purpose, which is not always the case. This sentiment is echoed by van Kessel *et al.* (2014), who allude to the ongoing risk of maintaining “fit for purpose” status (i.e., completeness, validity, consistency, timeliness, and accuracy) of enterprise data as it moves from the source to reporting. Meanwhile, there is considerable evidence of budget overruns in ICT projects, and the most common reason for this is poor system analysis and design (Mahony and Doran, 2008; Remenyi, Bannister and Money, 2017; Abdul-Samad and Kulandaisamy, 2022; Almarri, Boussabaine and AL Nauimi, 2023).

Moreover, the rate at which ICT changes relative to management accounting could lead to a mismatch between the ICT employed and the MCS in operation. Additionally, it may be challenging to determine the extent to which BDA influences MCS and vice versa (Seppänen, Saunila and Ukko, 2023). The above assertion remains the same when considering the use of BDA to facilitate MCS. This study focuses on BDA, which must be distinguished from the ICT ecosystem. Wang *et al.* (2024) describe BDA capability more concisely as an organisational capacity that blends technology, management practices, and human expertise to support data-driven decisions and innovation. Dzreke and Dzreke (2025) similarly describe BDA infrastructure as a

blend of human expertise, technological tools, and organisational routines, aligning it closely with socio-technical perspectives. It can therefore be justified to implicitly position BDA as a digital organisational capability, a socio-technical system, and a strategic resource embedded within wider ICT environments. Hence, the term ICT is used when referring to the broader technological environment, but the study's primary focus remains on BDA.

The complex nature of MCS and its intricate links with BDA question the mostly linear explanations produced by contemporary research (Granlund, Mouritsen and Vaassen, 2013). Additionally, most research has focused on the use of BDA to facilitate a single function of MCS. For example:

- BDA and decision-making (Król and Zdonek, 2020; Vitale, Cupertino and Riccaboni, 2020; Szukits, 2022; Franke and Hiebl, 2023)
- BDA and performance management (Reinking, Arnold and Sutton, 2020; Elbashir *et al.*, 2021; Montemari and Nielsen, 2021; Wielgos, Homburg and Kuehnl, 2021)
- BDA and value creation (Chammassian and Sabatier, 2020; Adriyendi, Putra and Defit, 2022; Laguir *et al.*, 2022)
- BDA and innovation (Curtis, Chui and Pavur, 2020; Ortiz de Guinea and Raymond, 2020; Schafheitle *et al.*, 2020; Pizzi *et al.*, 2021)

The literature review found no comprehensive study that examined the holistic approach to how BDA technologies can facilitate MCS. Therefore, it was essential for this study to develop a nuanced understanding of how BDA supports the functioning of MCS and how MCS design, in turn, mediates the operational and strategic demands imposed by BDA within the agri-food and beverage industry.

1.4 Research Question and Research Approach

This study aims to answer the following research question to address the gap in academic knowledge:

How do agri-food organisational actors interpret external pressures when using Big Data-enabled control systems, and how does this shape whether control practices are reinforced or changed: A strong structuration theory approach?

Literature from interlocking fields must first be explored to answer the research question. These interlocking fields are MCS and BDA, with a closer examination of their application in the agri-food and beverage industry. Otley (1999) identified two key objectives of MCS:

1. “To broaden the scope of information being considered beyond just accounting information. Paradoxically, it failed to achieve this, mainly because of its deliberate neglect of ‘operational control’” (p. 364).
2. To bring the issues of managerial motivation and behaviour into focus. This objective has proven more successful than the first, as evidenced by its “influence on behavioural management accounting” (p. 365).

Therefore, it can be argued that the effectiveness of MCS cannot be disconnected from the people who operate the system (Guenther, 2013; Liew, 2015). A typical MCS would seek to address three fundamental issues within an organisation:

1. Measurement of financial and non-financial activities within an organisation. Financial and non-financial activities are measured using relevant data from an effective information system. Non-financial measures are becoming an increasingly important part of MCS within contemporary organisations, and they may be used to overcome some of the perceived limitations in financial measures and to identify the drivers of performance (Chenhall, 2003; Malmi and Brown, 2008)
2. Informing and supporting decisions relating to resource allocation (Cugueró-Escofet and Rosanas, 2013)
3. Providing communication to and motivating staff through, for example, budgetary controls (Cugueró-Escofet and Rosanas, 2015; Drury, 2018)

These three issues form the basis for organisations to develop strategies to succeed and maintain a competitive advantage. Implementing business strategies can be overwhelming, just as developing them can be. The success or failure of any strategic implementation would depend on the control approach adopted. The overall goal is to ensure that all efforts (individual and collective) are defined and coordinated to fulfil the organisation’s objectives. These issues can be information-hungry and require the proper tool to extract information from various sources.

Thus, the research question was further developed to include the following objectives:

1. *How do industry-level analytical developments constitute external structural conditions that shape the use of management control practices in the agri-food and beverage industry?*
2. *How do organisational actors draw upon Big Data Analytics within their internal structures when implementing management control practices?*
3. *How do organisations' position–practice relations enable or constrain the use of BDA-enabled MCS?*
4. *How does the agency of management accountants contribute to the reproduction or transformation of control logics and data-driven decisionmaking practices over time?* (Rikhardsson and Yigitbasioglu, 2018)

1.5 Conceptual framework

A study of the application of BDA cannot be a linear cause-and-effect relationship, as many factors, such as people, strategies, and software/hardware, would determine its success. Also, since no two organisations will have the same strategy (Mintzberg, Ahlstrand and Lampel, 1998), it is crucial to acknowledge the impact of organisational context on the use of BDA to facilitate MCS. Therefore, identifying a framework suitable to evaluate the use of BDA to facilitate MCS across all food manufacturers is challenging. Hence, this study adopts Strong Structuration Theory (SST) as a framework that enables multi-layered analysis to reveal the nuances of using BDA to facilitate MCS in the agri-food and beverage industry.

Stones (2005, 2015) presents a framework for analysing a complex, web-like network of components within an organisation as they work together towards a common goal. SST offers a suitable framework for analysing complex relationships by examining how agents understand and respond to external structures and other actors in their context (Conrad, 2005; Englund and Gerdin, 2014; Feeney and Pierce, 2016, 2018). The framework aims to support researchers in deepening their understanding of how social norms, rules, and agencies influence organisational controls while also assisting managers in balancing formal controls with employees' adaptive behaviours. Coad et al. (2016) assert that researchers are more interested in the people (individually or collectively) and their analysis of their conduct and context using SST. This research

draws on this stance to gain deeper insight into the use of BDA to manage day-to-day finances, focusing on both users (agents) and the system (strategies).

1.6 Thesis Structure

Figure 1, below is a flowchart outlining the structure and logical progression of the research. It visually maps out how each chapter and concept builds upon the previous one, guiding the study's development.

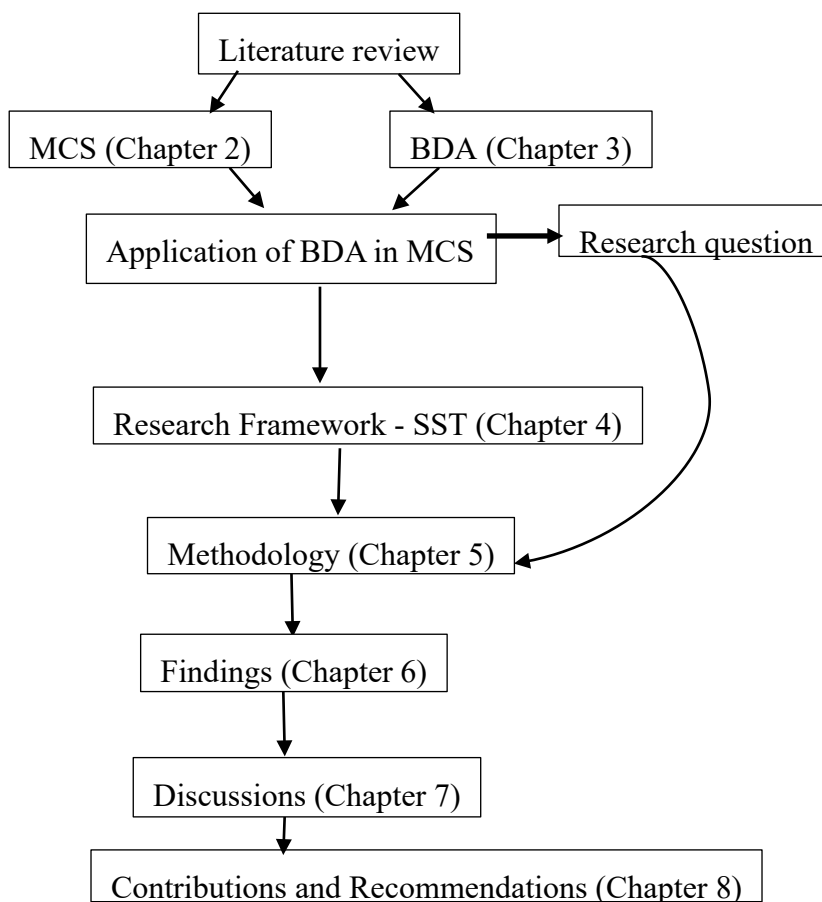


Figure 1: Thesis Roadmap (Source: Author)

The research begins with a literature review, where existing theories, models, and prior studies are examined. This sets the foundation for the research. The literature review for the study explores two key areas (core concepts):

Chapter 2 (MCS) and Chapter 3 (BDA) are treated as distinct but interconnected domains. The two branches converge into the review of the application of BDA in MCS. This section explores how BDA is applied within MCS, which forms the basis

of the research. Emerging from the integration of BDA and MCS, the study aims to identify the central issue or gap it aims to address.

Chapter 4 establishes SST as the research framework which guides the analysis and interpretation of data collected during the study. Chapter 5 details the research design, data collection, and analysis methods used to investigate the research question. Chapter 6 presents the research results, based on the methodology and framework, while Chapter 7 discusses their implications, aiming to draw conclusions, provide contributions, and offer recommendations. Chapter 8 concludes the study by summarising its impact, offering practical recommendations, and suggesting future research directions.

Chapter 2 Management Control Systems

2.1 Introduction

MCS is a formal and informal process, tools, and practices that organisations employ to ensure that employee behaviour and decision-making align with strategic objectives, thereby enabling efficient resource utilisation and objective attainment (Sa'adon, Amir and Amiruddin, 2019; Shakarchi and Nafzaoui, 2025). In other words, they are information-based procedures and techniques employed by managers to direct an organisation's activities towards predefined objectives (Anthony, 1965; Simons, 1991; Otley, 1994, 1999; Chenhall, 2003; Ferreira and Otley, 2009). The activities of an organisation usually depend on the resources available, including human, tangible, and financial resources, and on how these resources are matched to the organisational strategies pursued. A functioning MCS would ensure that adequate information is gathered to evaluate the effective use of organisational resources. Factors that motivate the use of ICT to facilitate MCS may be obvious, yet the barriers to achieving it are of utmost importance to companies, especially SMEs, which may not have the resources to spare.

A MCS has a much broader spectrum than traditional management accounting functions. Organisations exist in an environment of considerable uncertainty (Otley, 2016). Thus, a MCS operates in an uncertain environment and may need to adapt to these increasingly complex circumstances. To cope with uncertainty, organisations may make periodic changes, often to align disparate systems. Given the complexities in implementing MCS and its information needs, ICT tools may need to be employed to maximise the system's efficiency (Guruswamy *et al.*, 2022; Tavares, Azevedo and Marques, 2022; Habib *et al.*, 2024; Victor *et al.*, 2024).

MCS is highly diverse due to its broad spectrum and its operation in an uncertain environment, which may require adaptation to increasingly complex circumstances. As a result, a study involving MCS may be approached from either the theoretical traditions or functional perspectives. The traditional approach emphasises established theories and concepts, focusing on understanding underlying principles, assumptions, and theoretical implications. Meanwhile, the functional perspective is more practical and examines how MCS functions in real-world settings, including their roles, processes, and impacts on organisational performance (Simons, 1991; Otley, 1999; Chenhall, 2003; Malmi and

Brown, 2008; Ferreira and Otley, 2009). This study focuses on how BDA can facilitate MCS implementation, management, and improve its practice. Thus, the functional perspective is more relevant for this study.

The rest of the chapter begins with an analysis of the definition and evaluation of MCS, followed by an examination of the paradigms that govern MCS. These paradigms draw on Simons' (1995) levers of control. It is also essential to establish how MCS is linked to organisational strategies as well as the approach to designing and implementing MCS. The chapter also presents some applications of MCS from the perspectives of performance measurement and contingency theory. An analysis of potential challenges to implementing MCS is then followed by a conclusion summarising the chapter's highlights.

2.2 Definition and Evolution of Management Control Systems

Although theories on control date back to Taylor (1911) and Fayol (1916), Anthony (1965) refined control theory by distinguishing between strategic planning and management/operational controls, a distinction that became foundational in the MCS literature. His framework formalised a three-tiered hierarchy of controls as follows:

1. **Strategic Planning:** “the process of deciding on objectives of the organisation, on changes in these objectives, on the resources used to attain these objectives and on the policies that are to govern the acquisition, use, and disposition of these resources” (p. 16)
2. **Management Control:** “the process by which managers ensure that resources are obtained and used effectively and efficiently in accomplishing the organisation's objectives” (p. 17).
3. **Operational Control:** “the process of assuring that specific tasks are carried out effectively and efficiently (p. 18).

Subsequently, critiques and extensions of his framework have sparked considerable discussion about the definition and scope of MCS. A primary objection is that the framework is perceived as excessively hierarchical and stagnant, necessitating a more

dynamic approach that incorporates behavioural and social factors (Simons, 1991, 1995; Otley, 1994, 1999). For example, Otley (1994) argued that this traditional definition of the scope and practice of MCS, developed in the mid-1960s, was restrictive as it was based on large, hierarchically structured organisations, which were then, as now, in relative decline (Lee *et al.*, 2018; Prasad and Prasad, 2021; Vitali and Giuliani, 2024; Kulichyova *et al.*, 2025).

The definition of MCS has evolved over the years, shifting from providing more formal, financially quantifiable information to assist managerial decision-making to one that embraces a much broader scope of information (Chenhall, 2003; Haiza Muhammad Zawawi and Hoque, 2010; Bellisario, Appolloni and Ranalli, 2015; Johnstone, 2018; Akinola and Okundalaiye, 2022; Omar *et al.*, 2023; Walambuka, 2024). This evolution brings both clarity and ambiguity to the context in which the definition is used. In a typical modern organisation, management accounting, management accounting system, MCS and organisational control are sometimes used interchangeably (Chenhall, 2003; Chowdhury and Shil, 2023).

Malmi and Brown (2008) extend the concept of MCS as a package by proposing a novel typology for MCS with planning, cybernetic, incentive and compensation, administrative, and cultural controls. The typology differentiates between decisionmaking and control, focusing on the mechanisms managers deploy to regulate employee behaviour. Ferreira and Otley (2009) argue that challenges in the domain of MCS is generally complex and intertwined; however, research often relies on oversimplified and incomplete contexts. Such simplification facilitates research, but it can sometimes lead to greater ambiguity and conflicting findings across studies. Their concern was that the definition focused on formal, usually accounting-related, controls without situating them in their broader context. A comprehensive definition of MCS would have to consider the broader context in which a company operates (Otley, 2016; Brenner, Wald and Gleich, 2024).

Using contingency theory, Grabner and Moers (2013) established a clear distinction between management control as a package and a system, with the latter requiring conscious decisions about the design of interdependent controls. Their view is that a

MCS is a flexible tool that allows management to mould a control package already designed for the organisation. MCS is influenced by its contents, development trajectory, and traditional contingent factors (Otley, 2016). Therefore, a comprehensive study of MCS must consider the human impact and other external factors (Batt, 2025). Otley (2016) points out that organisations exist in an environment of considerable uncertainty. Thus, a MCS must be able to operate in such an uncertain environment and may need to adapt to cope with these increasingly complex circumstances. In addition, a MCS is often comprised of a series of subsystems that are surrounded by uncertainties (Janka, 2021). Changes may be made periodically to address uncertainties, usually to align dissimilar systems. Given the complexities of implementing MCS, tools such as ICT may need to be employed to maximise efficiency (Srivastava and Sushil, 2015).

Overall, MCS consists of formalised information-based procedures and techniques employed by managers to direct an organisation's activities toward predefined objectives (Anthony, 1965; Simons, 1991; Otley, 1994, 1999; Chenhall, 2003; Ferreira and Otley, 2009). The operations of an organisation often rely on available resources, including human, tangible, and financial assets, and on their alignment with the organisational strategies being implemented. An effective MCS requires the collection of accurate information to assess the efficient utilisation of organisational resources (Obaid, Awadh Bin-Nashwan and Abdullah, 2017; Omar *et al.*, 2023).

2.3 The paradigms that govern MCS

Given the inherent complexities of agri-food and beverage operations, developing a sound understanding of an organisation's MCS requires a detailed examination of its constituent components. Identifying the elements that constitute a standard MCS is fundamental to developing a coherent framework that guides its design, functioning, and integration within organisational processes. These paradigms range from the concept of systems and subsystems to the classification and control of these systems within various businesses. A typical MCS would seek to address the following issues within an organisation:

1. Financial and non-financial activities are measured using relevant data from an effective information system. Non-financial measures are becoming an increasingly important part of the MCS within contemporary organisations, and they may be used to overcome some of the perceived limitations in financial measures and to identify the drivers of performance (Chenhall, 2003; Malmi and Brown, 2008; Binh Bui, 2017; Janka, 2021)
2. Informing and supporting decisions relating to resource allocation (Cugueró-Escofet and Rosanas, 2015; Shaxson *et al.*, 2024)
3. Providing communication to and motivating staff through, for example, budgetary controls (Cugueró-Escofet and Rosanas, 2015; Drury, 2018; Mitter *et al.*, 2024)

Implementing business strategies can be just as overwhelming as developing them. The success or failure of any strategic implementation depends on the control approach adopted. The overall goal is to ensure that all efforts within the organisation, both individual and collective, are defined and coordinated to fulfil the organisation's objectives (Mintzberg, 1987; Kaplan and Norton, 1996; Porter, 1996; Grant, 2021; Smara and Bogatyreva, 2023).

Various frameworks have been designed to identify control system structures that effectively address some or all the issues facing a typical organisation. Otley (1999) elaborates on two key objectives of MCS:

3. "To broaden the scope of information being considered beyond just accounting information. Paradoxically, it failed to achieve this, mainly because of its deliberate neglect of 'operational control'" (p. 364).
4. To bring the issues of managerial motivation and behaviour into focus. This objective has proven more successful than the first, as evidenced by its "influence on behavioural management accounting" (p. 365).

Simons (1995) asserted the need for a new theory of control that recognises the need to balance these competing demands. According to Smara and Bogatyreva (2023), MCS can support innovative processes by providing the required control to ensure consistent behaviour while simultaneously fostering adaptation and creativity. Therefore, MCS must manage inherent tensions, such as the balance between freedom

and constraint, empowerment and accountability, top-down direction and bottom-up creativity, and experimentation and efficiency. Simons (1995) identified four key variables that govern how business strategy is controlled and developed them into the popular Levers of Control (LOC) framework. Simons' levers of control have been used in a variety of studies, which predominantly include performance systems and management accounting systems (Otley, 1999; Broadbent and Laughlin, 2009; Ferreira and Otley, 2009; Gani and Jermias, 2012; Arachchilage and Smith, 2013; Bedford, 2015; Wijethilake, Munir and Appuhami, 2018; Ogor and Fidelia, 2022; Burghardt and Möller, 2023; Weber, Pedell and Rötzel, 2024). Some studies have focused on the analysis of accounting information systems (Nicolaou, 2000; Hall, 2010; Weber and Roetzel, 2021), while others have predominantly been commentaries and analyses of LOC (Tessier and Otley, 2012; Martyn, Sweeney and Curtis, 2016). Simons outlines four interrelated control mechanisms that collectively generate dynamic tension within organisations: belief, boundary, diagnostic, and interactive control systems. Figure 2 presents these levers of control along with key variables that influence their impact on business strategies. The following sections discuss the levers of control and the variables associated with them.

The four levers of control can be depicted as follows (Simons, 1995: 7):

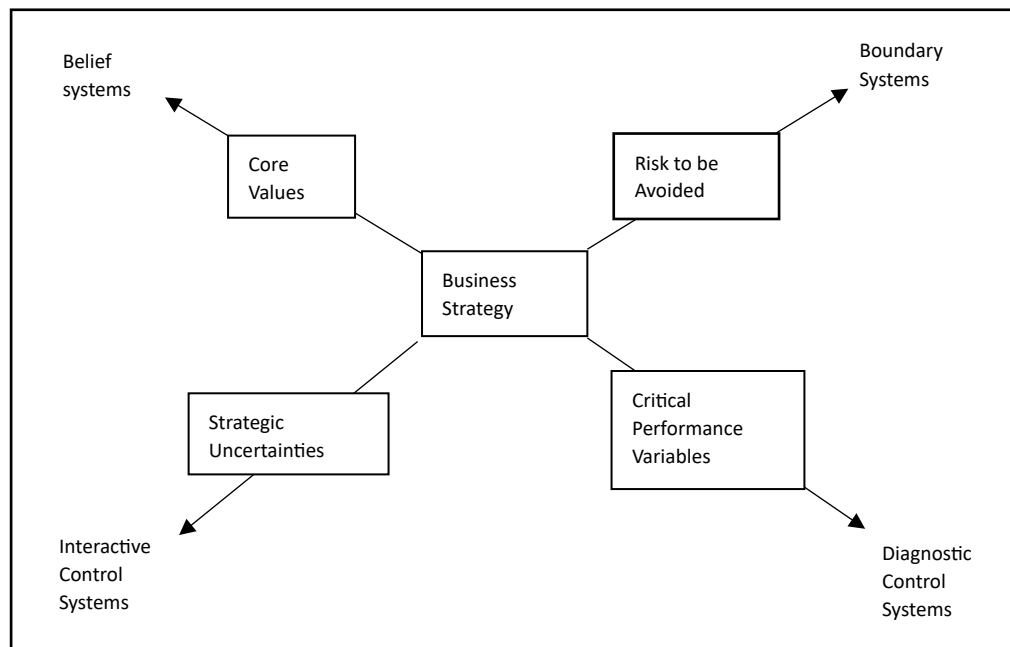


Figure 2: Controlling Business Strategy: Key variables that impact business strategies [source: Simons, 1995: 7]

2.3.1 Belief Systems

A belief system communicates core values that inspire and motivate employees to search, explore, create, and put in the effort necessary to engage in actions that lead to goal congruence (Widener, 2007). Belief systems inspire and direct the search for new opportunities, thus defining what the organisation has set out to do or achieve (Widener, 2007). Successful organisations are typically governed by their core values, which are usually enshrined in their constitutions or memoranda of association. Belief controls constitute an important type of control in SMEs that emphasise a flexible culture, as they are directly associated with this type of culture (Ogor and Fidelia, 2022; Rafifah *et al.*, 2023). Organisational culture can influence how people set personal and professional goals, perform tasks, and allocate resources to achieve them (Lok and Crawford, 2004). Thus, culture plays a vital role in defining an organisation's core values. A belief control provides a formal mechanism for communicating and translating the informal core values at the organisation's top to all organisational members (Simons, 1995; Lok and Crawford, 2004; Tucker and Parker, 2015). The responsibilities of top managers, as defined in belief systems, are to define, communicate, and reinforce the organisation's fundamental values, purpose, and direction. Managers must personally prepare substantive drafts of belief statements, which convey important messages about the organisation's future direction (Simons, 1995).

Belief systems are typically expressed through value statements that motivate people to engage in acts essential to the organisation's principles, purpose, and direction (Gerdin, Johansson, and Wennblom, 2019; Smara and Bogatyreva, 2023). Thus, organisations have formalised their belief systems and used them as formal control mechanisms, which guide the manner and direction in which employees work (Widener, 2007; Heinicke *et al.*, 2016). For example, new hires may be subject to a dual interview process, one of which concentrates solely on determining whether the applicant is a good fit with and will embrace the core values. Additionally, once hired, employees may be required to read and sign the company's code of conduct/operation to ensure they adhere to its core values. Belief systems form the foundation of organisational principles that guide and reinforce employees' behaviour towards the success of organisational strategies.

The belief systems are founded on three fundamental principles: mission statements (which establish corporate purpose), core values (which drive staff behaviour), and vision statements (which offer primary direction) (Akter, 2020). These fundamental principles form the basis for encouraging an entrepreneurial spirit within an organisation's employees (Bisbe and Malaguenõ, 2015; Knowles, 2025), but if left unchecked, organisational strategies might be compromised (sometimes unknowingly by overzealous employees). Therefore, some measures of checks and balances must be in place to prevent any overrun of the belief systems.

2.3.2 Boundary Systems

Despite the goal-congruence objective of belief systems, in dynamic environments, some restraint must be placed on employees to prevent them from engaging in high-risk behaviours (Widener, 2007). Simons (1994) defines boundary systems as formal systems that top management uses to establish explicit limits and rules that must be respected. These systems may limit opportunity-seeking behaviour (which an individual or a division of the organisation should avoid) to minimise the risk of deviation from the organisation's goals and objectives. For instance, a company operating in a high-risk environment or a highly regulated industry would likely adopt a boundary system to minimise the risk of employees making incorrect decisions on behalf of the organisation (Lill, Wald and Munck, 2020). This restraint is the boundary system, which opposes the belief systems (Widener, 2007). Organisational participants can view boundary systems as either constraining or liberating, and as Simons (1995: 39) states, "a boundary system delineates the acceptable domain of strategic activity for organisational participants". If participants perceive boundary systems as constraining, the primary aim of boundary systems shifts to preventing undesired actions and outcomes (Pianese, Errichiello, and da Cunha, 2023). The boundary model features administrative controls achieved through prohibitions, emphasising behaviour to be avoided, including prescriptive codes of conduct, and often carrying stringent penalties for non-compliance (King and Clarkson, 2015). Tessier and Otley (2012) define operational boundary control systems as a set of controls that inform employees of the limits imposed on their actions. These controls concern setting limits at the organisation's operational level. These limits can be communicated through

social controls, such as values, codes of conduct, or rules and procedures (Tessier and Otley, 2012). Boundary control systems may be viewed as either rewarding or punitive when applied to performance evaluation systems, depending on the subordinate's attitude.

The boundary and belief systems are similar in that they both aim to motivate employees to seek new opportunities; however, the boundary systems do so in a negative manner through the constraint of behaviours, while belief systems do so in a positive manner through inspiration (Widener, 2007). Boundary and belief systems may be used as complementary controls, with the adverse effect of one complemented by the positive impact of the other. This complementary property was highlighted by Simon (1965: 6) when he stated, “Organisations can accomplish this control objective through the balancing of multiple control levers in the LOC framework”. Strong boundary and belief systems are intended to counteract undesirable behaviour and minimise the adverse behavioural effects associated with strategic uncertainty (Weber, Pedell and Rötzel, 2024).

2.3.3 Diagnostic Control Systems

Generally, a company's mission or vision statement is entrenched in its constitution and communicated through belief systems, while its code of conduct represents its boundary system. A company's critical success factors are embedded in its diagnostic systems and communicated to its employees to motivate them to perform and align their behaviour with organisational objectives (Widener, 2007). Diagnostic control systems primarily motivate, monitor, and reward the achievement of specified goals. The diagnostic use of MCS represents the traditional feedback role, as the MCS is used on an exception basis to monitor and reward the achievement of pre-established goals (Henri, 2006). A diagnostic system may be considered a negative control lever because it draws managerial attention toward unfavourable variances and potential mistakes in implementing intended strategies (Bedford, 2015).

Eker and Eker (2016) noted that diagnostic control systems enable managers to effectively communicate the existing strategy to staff and implement it easily. However, in specific circumstances of dynamic competition, it can be limiting for

matters such as differentiation and expansion (Veliyath, 2025). It is generally accepted that managers should be responsible for creating and implementing new strategies; however, when controls are restricted to diagnostic control systems, this ability becomes significantly impaired. Simons (1987) asserts that diagnostic control systems offer features that are attractive to companies, such as monitoring effective resource allocation, reviewing past assessments, and saving time and labour in management. This assertion may not hold if subordinates cannot contribute their ideas to the strategy. Therefore, an MCS approach based exclusively on diagnostic control systems may lead to disputes and consequently miss pertinent issues (including uncertainties) that would otherwise contribute to the success or failure of a strategy (Rahman, Ahmed and Prideaux, 2024).

2.3.4 Interactive Control Systems

While the diagnostic system allows managers to manage results on an exception basis, an interactive system is forward-looking and characterised by active and frequent dialogue among top managers (Widener, 2007; Veliyath, 2025). An interactive control system helps the company strategically position itself in a dynamic marketplace, stimulating organisational learning and generating new ideas and strategies (Weber and Roetzel, 2021). Senior managers utilise interactive control systems to create internal pressure, break out of narrow search routines, stimulate opportunity-seeking behaviour, and encourage the emergence of new strategic initiatives (Arachchilage and Smith, 2013). Simons (1995) states that an interactive system is not unique; senior managers can use many control systems interactively. It has been recognised by Bisbe & Otley (2004), Henri (2006), and Widener (2007) that using interactive MCS can increase an organisation's potential to increase market share, innovation and other aspects of organisational learning. Although interactive MCS is likely to raise managerial tension (Widener, 2007), it is the most appropriate approach during a crisis or in situations of uncertainty (Simons, 1991).

In contrast to diagnostic control systems, interactive control systems are control systems based on dialogue between the top and subordinates. It can help companies develop new initiatives and strategies by causing them to focus on critical variables with provided coordination (Eker and Eker, 2016). As defined by Simons (1995), the

primary distinction between diagnostic control systems and interactive control systems lies in the “how” information is communicated between senior-level management and their subordinates. Therefore, diagnostic control systems and interactive control systems tend to be more appropriate in certain conditions than others. However, Simons (1991, 1995) recommends that a successful business strategy be achieved by integrating the four levers of control (belief systems, boundary systems, diagnostic control systems, and interactive control systems).

2.3.5 LOC – Benefits of combining the LOCs

Core values (which influence belief systems) and interactive control systems (which control strategic uncertainties) create positive and inspirational forces within organisations. Top management can adopt business strategies to turn threats created by strategic uncertainty into an opportunity for the organisation (Peçanha and Ferreira, 2025). As organisations constantly face threats from strategic uncertainties, management often employs interactive control systems that encourage employees to think critically, thus promoting learning. Adopting such a strategic approach would ultimately lead to a new strategic initiative. By choosing to use a control system interactively, top managers signal their preferences for search, ratify important decisions, and maintain and activate surveillance throughout the organisation (Simons, 1995)

In contrast, boundary systems (which control risks) and diagnostic control systems (which control critical performance variables) create constraints and ensure compliance with rules (Langfield-Smith, 1997). These systems have one main thing in common in that they are used to achieve an organisation’s strategic objectives. Each system is tied to a specific organisational situation and what the strategy in question intends to achieve. Each of the four levers of control is a potential contributor to the success of organisational strategies and complements the others in many ways. Simons (1995) argues that successful strategy implementation requires organisations to use all four levers in a balanced mix, depending on their circumstances. Ferreira and Otley (2009) reinforce this point by asserting the significance of examining all four levers of control for understanding the core concepts of MCS. Kruis, Speklé and Widener (2016) cast doubt on the claim that control systems must be balanced to manage competing tensions, such as that between predictable goal achievement and

innovation. This argument helps to clarify, not refute Simons' (1995) suggestion that the levers of control work better when implemented together. Besides, these levers are deliberately designed to create productive tension, which can be affected or ineffective depending on the balance of the controls. Paradoxically, Andriopoulos and Lewis (2009) argue that competing tensions are persistent and interdependent, not trade-offs to be resolved. The stability of diagnostic control needs to be balanced with the flexibility of interactive control, which supports innovation and manages strategic uncertainty. Organisations without this balance risk becoming either too rigid or too chaotic. Therefore, Kruis, Speklé and Widener (2016) appear to test "balance" empirically while overlooking its theoretical importance in the underlying design logic. Control systems operate within established position–practice relations, and they should work to reduce strategic bias and power imbalances so the organisation can function more effectively. Because the agri-food and beverage industry faces high uncertainty but still needs innovation, companies must balance their control systems to support innovation in an unpredictable environment.

2.4 MCS and strategy

The definition of strategy may initially seem straightforward, but it depends on the context in which it is used. Mintzberg (1987a) suggests that the definition of strategy would be linked to the concepts of the plan (which could be a ploy as well), pattern (of action), position (competitive), and perspective (overall). A strategy may therefore be defined as a plan of action (general or specific) to maintain a competitive advantage by achieving certain goals and using a stated approach.

Contemporary discourse on competitive strategy emphasises methods by which businesses can establish imperfectly competitive product markets to achieve superior economic performance (Rostek and Yoon, 2024); however, the cost of executing these strategies is as critical as the creation of the markets themselves (Liu and AtuaheneGima, 2018). Strategy varies across industries, and even within a given industry, it varies among companies. As primary objectives may vary across departments, companies, and industries, so does the strategy used to achieve them. Strategy will also likely vary across different departments within the same organisation. LangfieldSmith (1997) described strategy as a pattern of decisions about

the organisation's future that takes on meaning when implemented through the organisation's structure and processes. Strategic management can be defined as the identification of an organisation's purpose and the plans and actions required to achieve that purpose (Lynch, 2015). Management control is key to the success of every organisation, as it provides the focus for all activities that ensure overall operational coherence and that the organisation retains the capability to survive in its uncertain environment (Otley, 1994). A successful strategy depends on management control; hence, top management's key focus is on MCS. MCS is central to developing management practices that can match the needs of contemporary organisations (Chowdhury and Shil, 2023). Otley and Berry (1980) also pointed out that an effective MCS depends on three key components: goal alignment, adaptability, and integration. Effective MCS needs to be linked to the organisation's strategic objectives and be adaptable to an ever-changing environment to ensure the organisation's overall functioning (Rischar, 2023).

Lynch (2015) mapped out what he described as the future direction that needs to be adopted for the resources possessed by the organisation. He also stated that strategic management consists of three main levels: corporate, business, and operational. Corporate-level strategy concerns decisions about the types of businesses to operate. In contrast, business-level strategies relate to each business unit of the organisation and focus on how individual SBUs (Strategic Business Units) compete within their particular industries (Langfield-Smith, 1997). Lynch (2015) proposed some essential points on strategic management that could be incorporated into the design of an MCS. Table 1 lists common concerns that businesses use to assess their aims and objectives at both the corporate and strategic levels. The design and implementation of MCS address these difficulties while taking into account organisational features such as the nature of the business, culture, size, and structure.

At the general corporate level:		At the individual business level:
What business are we in? What business should we be in?		How do we compete successfully? What is our sustainable competitive advantage?

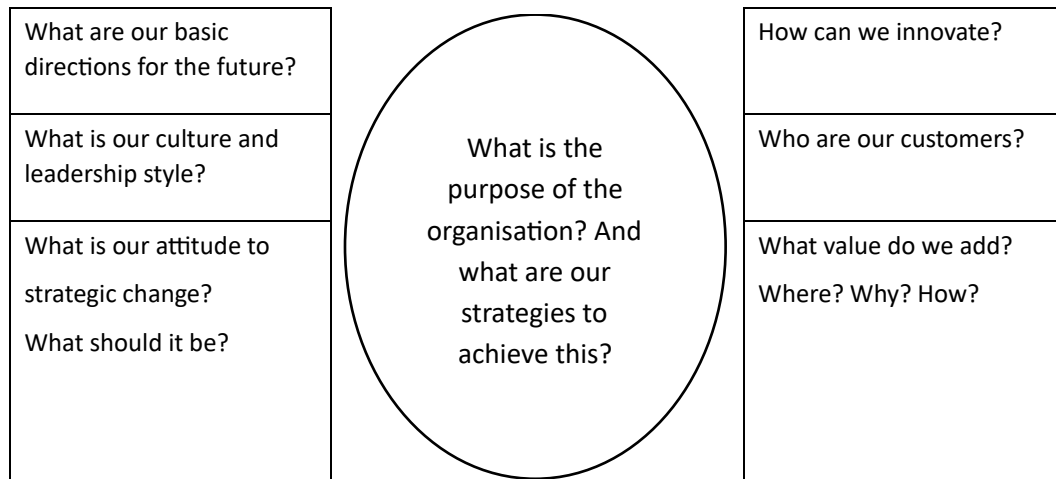


Table 1: The essence of strategic management [Source: Lynch (2015: 8)]

The third component of a strategy is found within an organisation's operational functions. It may be considered the key ingredient to the success of both corporate and business-level strategies. Operational strategies address how the organisation's various functions contribute to the business strategy and competitiveness (LangfieldSmith, 1997).

To successfully test the strategic fit of an MCS, outcomes may need to be separated into issues related to the use or usefulness of the MCS and behavioural and organisational outcomes (Chenhall, 2003; Chowdhury and Shil, 2023). Even a well-designed MCS (tied to the organisation's strategies) may not achieve the objectives set out in the strategy due to management behaviour or organisational constraints. For example, in certain circumstances, top managers use control systems daily to intervene in organisational decision-making, thereby depicting the control system as interactive rather than diagnostic (Simons, 1991). While diagnostic control systems constrain innovation and opportunity-seeking to ensure the predictable goal achievement for intended strategies, other MCS produce the opposite effects (Simons, 1995; Lill, Wald and Munck, 2020). A MCS that enforces rules may not benefit all organisations and circumstances. Interactive control systems stimulate search and learning, allowing new strategies to emerge as participants throughout the organisation respond to perceived opportunities and threats (Wrubel, Silva and Toigo, 2022). The power of interactive control systems lies in allowing management to adjust to circumstances within and outside the organisation (Andersen, 2015).

It is common knowledge that organisations do not operate in isolation. Therefore, their environment often influences organisational strategies, both positively and negatively. Simons (1991) suggested that, in addition to behavioural and organisational influences, strategic uncertainty also plays a key role in the success or failure of a control system. Unlike the previous studies, which took a more interpretive approach, Simons' model adopts a more functionalist approach to explaining the relationships between MCS and strategy (Langfield-Smith, 1997). The relationship between business strategy and control can be represented in Figure 3

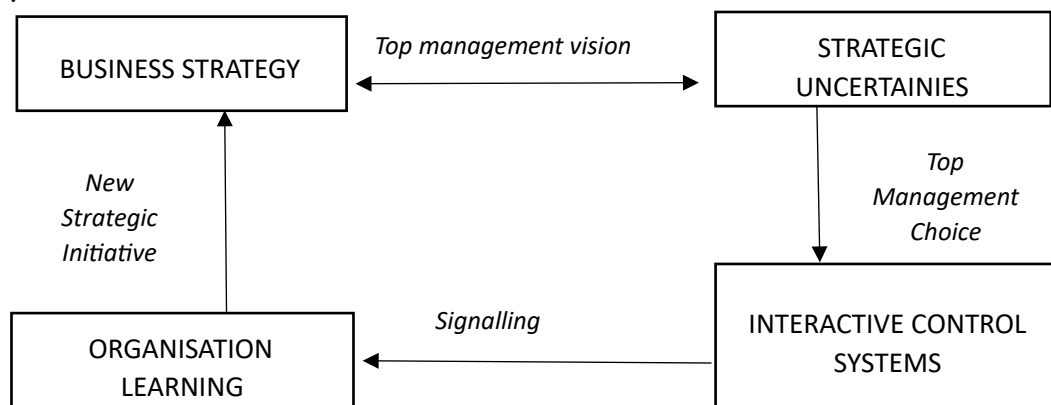


Figure 3: A process model of the relationship between business strategy and control [Source: (Simons, 1991 p. 50)]

In general, MCS is often associated with the strategies employed by individual companies. Most research on the relationship between MCS and strategy focuses on business strategy (Simons, 1987, 1991; Adler, 2011; Arachchilage and Smith, 2013; Arjaliès and Mundy, 2013; de Harlez and Malagueño, 2016). However, there is an increasing interest in considering the nature of MCS and operational strategies (Omar and Kilika, 2018; Ai and Ziehl, 2024; Hammouch, 2024; Basra, Wedawatta and Tetteh, 2025).

Even a well-developed strategy may fail in execution if it adopts the wrong implementation approach. Gani and Jermias (2012) recognised that strategy-MCS misfit is measured by the degree to which the observed configuration deviates from the optimal configuration for a given strategy type. When such deviations are identified, management tends to focus on resolving issues arising from these anomalies, thereby neglecting more positive alternative outcomes and labelling MCS as a diagnostic control system (Simons, 1991). For example, variance analysis tends

to focus on adverse variances (Alli-Momoh *et al.*, 2024), while giving less consideration to the favourable variance that may have arisen from initially setting incorrect standards (Drury, 2018). Contrary to this general perception, research has indicated that control systems are not always used to manage by exception (Simons, 1991). It is logical for management to pay more attention to issues that deviate from or inhibit the successful implementation of strategic organisational objectives.

2.5 Approaches to MCS design and implementation

As identified in the previous section, there is an implied connection between strategic organisational objectives and the outcomes of a control system. The view is that a successful MCS depends on how management uses the information provided by the system and on the level of responsibility entrusted to the manager. If MCS is helpful, it will likely provide satisfaction to individuals who can presumably approach their tasks with enhanced information (Chenhall, 2003). The success of MCS depends on its ability to facilitate information sharing across various levels of management within the organisation, as shown in Figure 4. The central tenets of the success of an interactive control system were captured by Simons (1995) in a schematic representation of the flow of information within the various levels of organisational management.

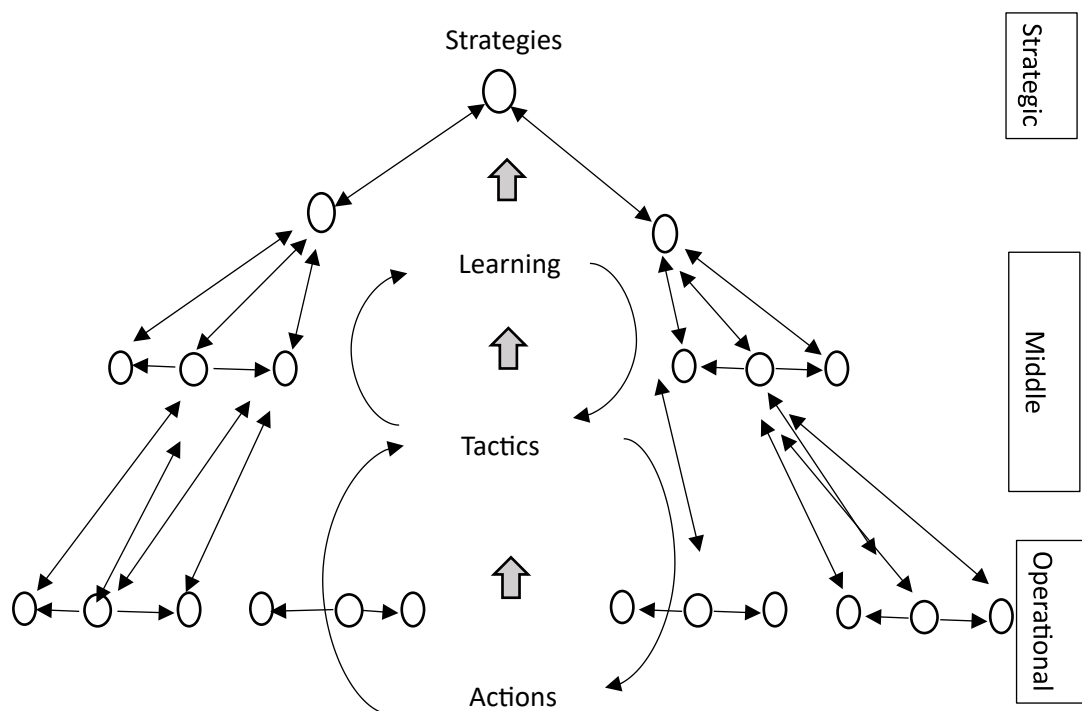


Figure 4: Interactive Control Stimulates Information Sharing and New Strategies [Source: (Simons, 1995: 103)]

Because of the intricate web produced by the interconnectivity of information flow across levels and within the same level, top management must monitor the flow of information and its utilisation. If all information channels are left open to all participants at all levels, they would be open to abuse, consciously or unconsciously due to lack of experience or knowledge. In an organisation with multiple control systems, Simons (1995) believes that at least one of the systems should be used interactively. For example, a budget that would be implemented interactively should involve managers at all levels. Other activities (such as determining new market expansion) will be diagnostically controlled by management at the strategic level to ensure their implementation aligns with the organisation's strategic objectives.

Simons (1987) identifies four key conditions that would usually be present when control systems are used interactively (on a day-to-day basis), which are:

1. The information generated by the MCS is an important and recurring agenda item addressed by the highest levels of management
2. The process demands frequent and regular attention from operating managers at all levels of the organisation
3. Data is interpreted and discussed in face-to-face meetings with superiors, subordinates and peers
4. The process relies on the continual debate over underlying data, assumptions, and action plans.

If these conditions are applied correctly, they can help companies achieve their strategic objectives. Although interactive control systems are frequently associated with a singular strategic issue (Gomez-Conde *et al.*, 2023; Lewis, Sutton and Brown, 2024) and serve as a medium for feedback and learning rather than merely performance monitoring (Lillemets *et al.*, 2025), Simons' framework continues to be fundamental in MCS (Cardoni, Hiebl and Paradisi, 2023).

An organisation monitors the validity of its strategy using indicators that track changes in the external environment that could invalidate the current strategy (Tessier and Otley, 2012; Ferry and McMaster, 2018; Hao, 2024). These processes are usually

iterative, going from condition one to four and back to one again until perfection is achieved. For example, introducing new technology begins with analysing system requirements aligned with the organisation's strategies. The analytical process requires talking to managers and employees to develop a system that best fits the organisation's operations. Once the system has been analysed, developed, and implemented, an evaluation follows to identify any variances or errors and to take corrective measures. Hence, Tessier and Otley (2012) concluded that this control could be used interactively or diagnostically. For example, an intensive discussion during meetings to direct managers' attention is considered a form of interactive control. Meanwhile, focusing on learning from incremental changes introduced by the new system and thus adapting the strategy is an example of diagnostic control. As depicted above, for a new strategy to succeed, interactive controls can be used to stimulate information sharing, and diagnostic controls can be employed to evaluate the strategy's implementation.

2.6 Application of MCS

2.6.1 Performance Measurement

As defined earlier, strategic management is the identification of the purpose of the organisation and the plans and actions to achieve that purpose (Lynch, 2015). A well-designed measurement system must be in place to evaluate an organisation's goals and objectives. A formal performance measurement system is seen as a significant mechanism for making explicit the set of means-end relationships that the organisation has developed, as well as the methods it will use to implement its strategic intent (Otley, 1999). Since the goals and objectives are clearly stated, formal performance measurement systems tend to be mostly quantitative and objective (Hartmann and Slapničar, 2009). As mentioned above, the success of business strategies hinges on the successful execution of operational activities. The operational performance control system focuses on critical performance variables at an operational level (Tessier and Otley, 2012).

2.6.2 Contingency Theory Approach to MCS Implementation

The success of any organisational strategy depends on multiple factors shaped by the organisation's goals and objectives. These goals and objectives themselves depend on other limiting factors, some of which are uncontrollable. Otley (1980) pointed out that

contingent theorists have been chiefly concerned with finding the exact features of an organisation's situation that impact specific features of MCS design. Researchers have attempted to explain the effectiveness of MCS by examining designs that best suit the nature of the environment, technology, size, structure, strategy and national culture (Chenhall, 2003; Dimitrios and Athanasios, 2014; Moonen, 2017; Hammouch, Manta and Palazzo, 2024). The effectiveness of an MCS depends on the interplay of these parameters and the management accounting system used.

Many researchers on the relationship between MCS and strategy have recommended greater attention to 'how' MCS is used rather than 'the degree' it is used (Janka, 2021). Empirical research on MCS has tended to adopt a contingency approach in seeking effective relationships between typical MCS elements and an organisation's specific strategy (Langfield-Smith, 1997). Contingency theory holds that a company's performance depends on the alignment of various organisational factors within a given business context (Duréndez *et al.*, 2016). Otley (2016) analyses contingency theory as applied to MCS and developed the contingency school of thought, which states that there is no single, universally valid MCS. Instead, the appropriate design depends on several factors relating to organisational objectives, the environment in which the organisation operates and the organisation's (internal) structure.

A typical MCS has to adapt to circumstances particular to the organisation (its objectives, internal structure and the environment in which it operates). Appropriate control systems should be open and informal and include broad-scope information, benchmarking, and performance measures that indicate links between strategy and operations, such as balanced scorecards and strategic integrative controls (Chenhall, 2003). In general, approaches to MCS design are often contingent upon the organisational type, operating environment, culture and industry (Speklé and Widener, 2020; Hammouch, Manta and Palazzo, 2024). When designing an MCS, Otley (1994) recommends that the scope of observation be broad enough to encompass control activities ranging from selecting personnel, management and organisational development practices and business process re-engineering techniques to the more traditional ideas of performance measurement and appraisal. Otley (1999) later argues that MCS should provide valuable information to managers in performing their jobs

assisting organisations in developing and maintaining viable behavioural patterns. Therefore, a system approach to contingency theory maintains that organisational design involves two basic choices: (1) selecting MC practices that match the set of contingencies facing the organisation (Janka, Heinicke and Guenther, 2020) and (2) assuring that the MC practices are internally consistent (Janka, 2021).

2.7 Possible Challenges to MCS

One of the primary objectives of MCS is to expand the scope of information provided to management, enabling them to make informed decisions; however, this information can sometimes be overwhelming. Chenhall (2003) critically reviewed findings from contingency-based studies over twenty years in an attempt to explain the effectiveness of MCS by focusing on different types of MCS designs. He gathered that MCS designs should best suit the nature of the environment, technology, size, structure, strategy and national culture (Chenhall, 2003). These elements present different challenges depending on the organisation and the environment in which it operates.

Traditional MCS is often criticised for information flowing from top to lower management, leaving less room for subordinates' innovation. In some situations, only the manager can supervise, encourage and control the company's employees. Logically, the manager cannot be everywhere, so some loopholes are bound to arise. To resolve this issue, traditional MCS requires assigning responsibilities to subordinates, who must report to top management (Prayudo *et al.*, 2023; Bauer and Greiling, 2025). In addition, traditional MCS focuses on sales, profit, and output, while paying less attention to other important business components, such as innovation (Bobe and Teklay, 2025). The command-and-control rhetoric that dominated management accounting in the 1960s-1990s no longer suffices in competitive environments where creativity and employee initiative are critical to business success (Simons, 1995). Modern MCS is more adaptable to the changing business environment, coping with challenges and taking advantage of opportunities presented (Porath, 2023). Today, MCS is quite flexible and often adapts its workflow to incorporate new developments, thereby increasing innovation (Janka, 2021). MCS often focuses on developing its employees' knowledge, skills, and abilities, both as a team and individually, to foster goal congruence (Dana, Rounaghi, . Current principles of MCS aim to align an individual's motivation with the company's goals, often

providing employees with opportunities to solve problems, thereby empowering them to take action proactively. Due to their flexibility and adaptability, modern MCS is more likely to employ technology in its implementation, thus resolving most of the issues raised by traditional MCS (Silva *et al.*, 2025).

A MCS aims to measure organisational performance, support resource-allocation decisions, and communicate with and motivate staff through mechanisms such as budgets. Organisations build strategies around these three issues to stay competitive, but both designing and implementing a strategy can be demanding. The outcome largely depends on the control approach used, which must align individual and collective efforts with organisational goals. Because these issues require extensive data, organisations need effective tools to gather and analyse data from multiple sources, which necessitates BDA.

2.8 Conclusion

Most of the studies on MCS have been linked to Simons' (1991) levers of control, which identify four pillars of MCS: belief, boundary, interactive, and diagnostic control systems. Simons (1991, 1995) recommended that a successful business strategy be achieved by integrating the four control levers. MCS implementation strategy is highly linked to organisational strategy (Otley and Berry, 1980; Simons, 1987, 1991, 1995; Otley, 1994; Lynch, 2015; Ogor and Fidelia, 2022), organisational structure (Langfield-Smith, 1997; Chenhall and Moers, 2015; Lynch, 2015; Giacosa, Culasso and Crocco, 2022) and also takes into consideration environmental and company-specific challenges (Anthony, 1965; Chenhall, 2003; Otley, 2016). MCS has been researched from a variety of lenses, ranging from performance measurement (Otley, 1999, 2003, 2016; Lill, Wald and Munck, 2020; Silva *et al.*, 2025; Sissah and Hmioui, 2025) to strategic fit (Langfield-Smith, 1997; Chenhall, 2003; Speklé and Widener, 2020; Janka, 2021; Porath, 2023), as well as its integration with accounting information systems (Nicolaou, 2000). Meanwhile, the impact of BDA on MCS has been examined to a degree; nevertheless, limited empirical research has been conducted about the levers of control, despite substantial evidence of their significance in strategic implementation (Simons, 1994, 1995; Tessier and Otley, 2012; Heinicke, Guenther and Widener, 2016; Kruis, Speklé and Widener, 2016).

Chapter 3 Big Data Analytics

3.1 Introduction

This chapter analyses the literature on the influence of Big Data on MCS within an organisation and its subsequent impact on organisational-level MCS. Although in a typical modern business, the terms management accounting, management accounting system, MCS and organisational control are sometimes used interchangeably (Chenhall, 2003), there have been considerable studies on the relationship between these key components (Bisbe et al., 2007; Jack et al., 2018). It has also been established that ICT can assist in implementing MCS (Granlund, 2011; Granlund et al., 2013; Quattrone, 2016).

Given the trends in the growth of data, it has become imperative for businesses to develop the capability of extracting information from various data sources, hence the concept of big data (Chen, Chiang and Storey, 2012; Moffitt and Vasarhelyi, 2013; Bhimani and Willcocks, 2014; Warren, Moffitt and Byrnes, 2015). Big data technologies facilitate data collection, analysis and information delivery and are designed to support decision-making (Rikhardsson and Yigitbasioglu, 2018). Since decision-making is one of the prime functions of MCS, which relies on relevant and timely information, the concept of big data, therefore, represents a social movement or cultural shift in organisations that implement data-driven decision-making (ChowWhite and Green, 2013). The trend toward big data and analytics (BDA) for business intelligence provides excellent resources and robust methodologies to support the data-driven decision-making process, which is the core of business intelligence (Liang and Liu, 2018).

BDA's influence on MCS has been studied to some extent, but few empirical studies have been carried out about the levers of control, despite the overwhelming evidence of their importance to strategic implementation (Simons, 1994, 1995; Tessier and Otley, 2012; Heinicke, Guenther and Widener, 2016; Kruis, Speklé and Widener, 2016). All four control levers require specific information for implementation, and BDA provides the tools to extract it from data. The rest of the chapter begins with evaluating the definition and evolution of big data. Then follows an analysis of the various types of analytics that can be applied to big data. A refocus on how BDA aligns

with organisations' strategies, followed by a discussion of some common BDA themes as applied to MCS, including challenges to the strategic use of BDA. The chapter concludes with a description of the approach used to review the use of BDA in MCS.

3.2 Definition and evolution of big data

In recent years, the expression “Big Data” has become more prevalent in academic research, while “Business Intelligence” was introduced much earlier. Business Intelligence was first coined by Luhn (1968) when he described it as a system that would utilise data-processing machines for auto-abstracting and auto-encoding documents and create interest profiles for each of the "action points" in an organisation. His definition revealed the flexibility of such a system in identifying general information, determining who needs to know it, and disseminating it efficiently, either in abstract form or as a complete document. The integration of this concept into decision support and information systems was not suggested until later, when Vitt et al. (2002) describe Business Intelligence as a multifaceted concept that covers three different perspectives. These perspectives were identified as enabling faster, better decisions, converting data into actionable information, and employing a rational approach to management. These perspectives tie in neatly with the BDA-cycle (Figure 5), which is thought to include four phases: analysis, insight, action, and performance measurement (Vitt, Luckevich and Misner, 2002).

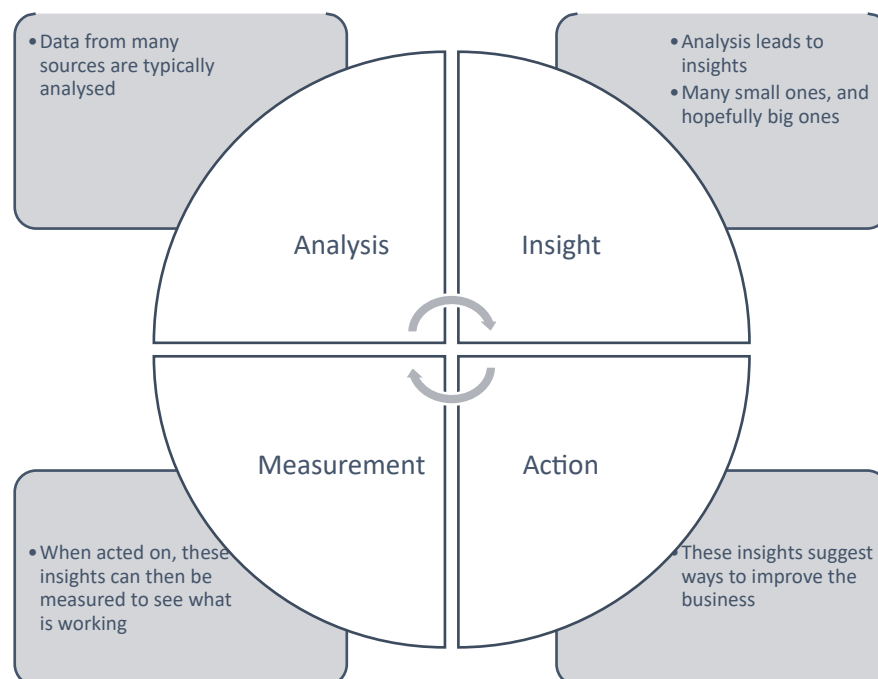


Figure 5 The BDA cycle [adapted from Vitt et al. (2002)]

The successful implementation of this cycle is limited by what Vitt et al. (2002) described as the analysis gap, the large gap between the information that decisionmakers require and the masses of data businesses collect daily. Data collection and analysis techniques like data warehousing, data acquisition, data mining, business analytics and visualisation were introduced to help resolve this barrier (Turban, Aronson and Liang, 2005; Liang and Liu, 2018).

With the continuous increase in data volume and variety, the concept of big data has become prominent, reflecting the complexity of the data. There have been various definitions of this concept (Vitt et al., 2002; Liang and Liu, 2018). Due to the conflicting definitions of big data among various stakeholders, including academia, industry, and the media, it is challenging to find a single, agreed-upon definition. The key characteristics of big data have formed the basis of most definitions to date. For example, Manyika et al. (2011) refer to big data as datasets whose size exceeds the capabilities of typical database software tools to capture, store, manage, and analyse. This definition is subjective and time-bound, as datasets considered large today may become normal later as more powerful database systems emerge. For example, a onegigabyte video file is normal today, whereas the same file size would have been considered too large decades ago, when data storage capacity was limited. Size is the first characteristic that comes to mind when considering the question “What is big data?”; however, other characteristics of big data have emerged (Gandomi and Haider, 2015). The volume of data available to businesses has increased exponentially over the last decade, and the variety has not made it any easier for data-centric decisionmakers. The main characteristics were then initially identified as volume, velocity and variety (Laney, 2001; Chen, Chiang and Storey, 2012), but have since been extended to include veracity, variability and value (Gandomi and Haider, 2015; Vasarhelyi, Kogan and Tuttle, 2015; Appelbaum, Kogan and Vasarhelyi, 2017; Murthy and Geerts, 2017; Mariani *et al.*, 2018)

Hashem et al. (2015: 100) presented a holistic definition as “Big data is a set of techniques and technologies that require new forms of integration to uncover large hidden values from large datasets that are diverse, complex and of a massive scale”. The literature presents a range of characteristics to describe big data, which can be summarised as follows (the Vs of Big Data):

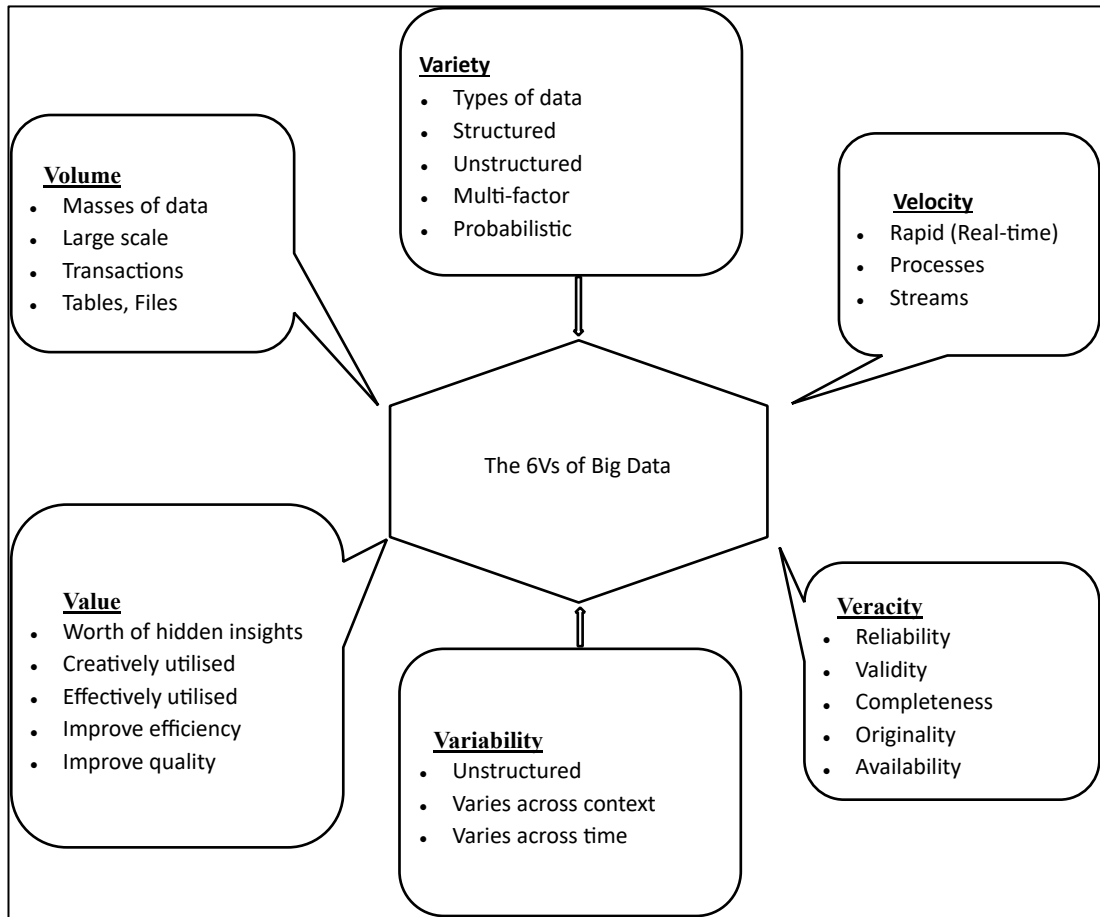


Figure 6: Compiled from various sources (Source: Author)

As the debate continues, more characteristics of big data are being proposed, building on the 6Vs (Figure 6). For example, Tonidandel, King and Cortina (2018) suggest that the aspect of velocity that concerns the latency of data is assigned its own V with V standing for Viscosity in this instance. Similarly, as data extraction techniques enter the AI era, Alyasiri, Akhtom, and Alrasheedy (2023) expand the list of big data characteristics to include validity, venue, and vagueness. They contend that validity is a crucial attribute of big data, helping authenticate data sources and enhance data integrity. Furthermore, the globalisation of businesses has resulted in data sources

being distributed across several geographical regions. In this context, venue is a crucial aspect of big data, as it influences data scalability, enabling processing options that are not limited by geographical constraints (Alyasiri, Akhtom and Alrasheedy, 2023). With the proliferation of data sources, data scientists are increasingly confronted with ambiguous or imprecise data, which has led to the inclusion of vagueness among the attributes of big data. Lewis and Martin (2015) suggest that big data is prone to vagueness and uncertainty, while Tenali and Babu (2023) echo this, attributing it to the big data tools used. Vocabulary has been suggested as another attribute of big data (Alyasiri, Akhtom and Alrasheedy, 2023), referring to the specific language and terminology associated with a dataset. This characteristic is even more important in the era of AI, which requires encoding text for search engines. The definition of big data is therefore characterised by 10Vs, of which six are core (Figure 6), and the others are derived from these initial ones.

From the MCS perspective, big data refers to information sources other than traditional data. However, the main challenge for management accountants is extracting the information needed to create value. The value of information generated by various types of analytics may increase with the complexity of the data analytics process. The directly proportional relationship observed in the comparison of business value derived from various types of analytics enables BDA to influence MCS in diverse ways.

3.3 Types of Analytics

BDA involves analysing large, complex datasets to uncover hidden patterns, correlations, trends, and insights. Acknowledging the specifics of modern BDA applications (i.e. descriptive, predictive, and prescriptive applications) can help separately analyse the impact of specific analytics methods, techniques, and models on various facets of performance (Ashrafi *et al.*, 2019). Various categories of BDA exist, each serving distinct objectives, as shown in Figure 7.

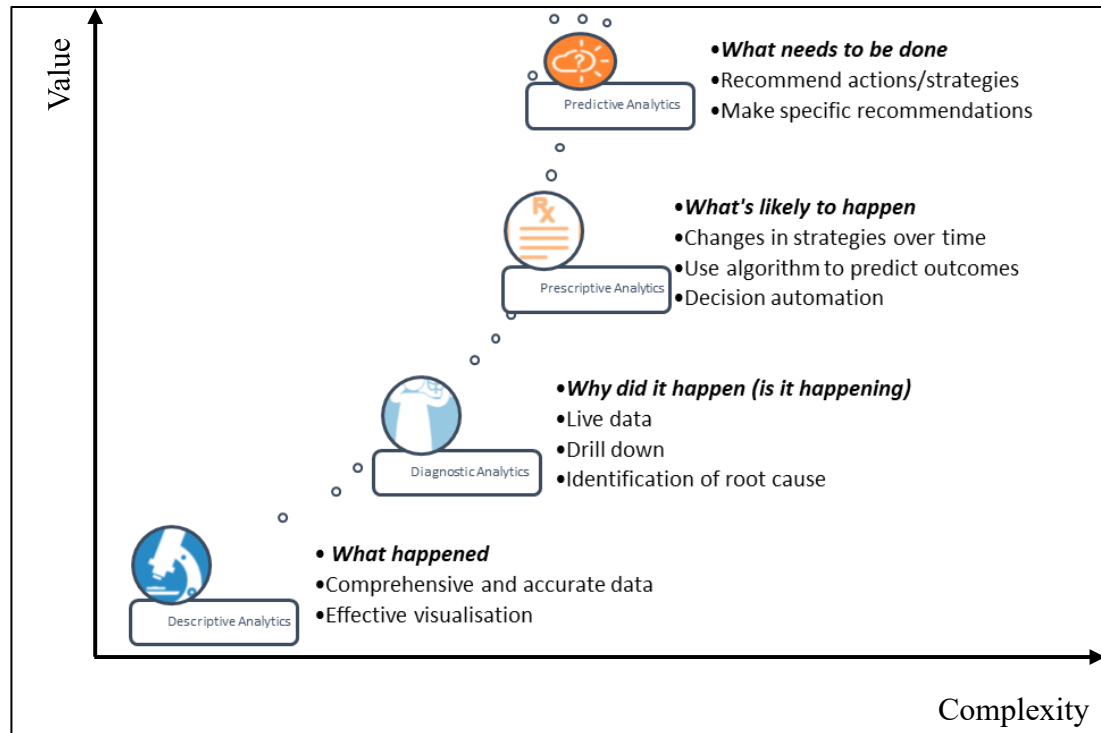


Figure 7: Types of business analytics – built from various sources (Source: Author)

3.3.1 Descriptive Analytics

Descriptive analytics summarise what has happened and form the basis of many continuous monitoring alert systems. Transactions are compared to benchmarks, and thresholds are established from ratio and trend analysis of historical data (Appelbaum, Kogan, Vasarhelyi et al., 2017). With the help of enablers such as business reports, graphs, charts, dashboards, scorecards, and data warehousing, this type of analytics seeks to answer questions like what happened or what is happening (Sarker, 2021; AlKhatib, 2025). The resulting outcomes from this type of analytics often include welldefined business problems and opportunities by providing context to help managers interpret information (Dai *et al.*, 2020). Descriptive analytics synthesises raw data from multiple data sources into meaningful information that provides valuable insights into the past. Quality control is a crucial part of the strategies of agri-food and beverage companies, and it will benefit from descriptive analytics. For example, data from a bakery oven might indicate whether it is operating at the expected optimal level. Meanwhile, these results may indicate that something is wrong or right without explaining why it happened. Descriptive analytics provides comprehensive and accurate data that facilitate effective visualisation, making it easier to transform this information into meaningful insights (Kharakhash, 2023; Wolniak,

2023). On the other hand, the information generated by this type of analytics is less relevant for decision-making without the application of additional analytical techniques. Therefore, descriptive analytics is positioned at the lowest end of the analytics spectrum compared to the other types.

3.3.2 Diagnostic Analytics

Diagnostic analytics is considered an extension of descriptive analytics, which reports the past and seeks to answer questions such as “Why did it happen?” (Soltanpoor and Sellis, 2016; Sarker, 2021). Diagnostic analytics is a thorough examination of data to ascertain the underlying causes of events and behaviours (Dai *et al.*, 2020). Data from descriptive analytics provides a foundation for an analyst to drill down using diagnostic analytics tools to isolate the root cause of a problem. For example, descriptive analytics of data from an oven in a bakery may indicate that the oven is operating at a temperature below the set point. However, a deeper analysis using diagnostic analytical tools may reveal whether the setting configuration is incorrect or whether the output data is incorrect. Diagnostic analytics uses historical data to compare against benchmark data, answering questions such as “Why did something happen, or is it happening?” Building on the previous example, the benchmarking data would be taken from the manufacturer’s manual or previous operational data of the same oven. Diagnostic analytics tools use live data and a drill-down into historical data to identify the root cause of issues (good or bad) relating to business strategies. The diagnostic analytics process is efficiently employed in machine health monitoring, prognosis, fault detection, and maintenance (Ajah and Friday Nweke, 2019). This process is more complex than descriptive analytics and generates more business value by providing information to improve decision-making. It helps organisations to understand relationships among different kinds of data, thus grasping the reasons behind the events that happened in the past (Soltanpoor and Sellis, 2016).

3.3.3 Predictive Analytics

Predictive analytics builds on the knowledge acquired from descriptive analytics to answer the question of what could happen (Appelbaum, Kogan, Vasarhelyi *et al.*, 2017). Predictive analytics seeks to uncover patterns and capture relationships in data (Gandomi and Haider, 2015; Labro, Lang and Omartian, 2023) to predict whether an

event will happen, when it is about to happen and why (Lepenioti *et al.*, 2020). Soltanpoor and Sellis (2016) describe predictive analytics as a “forecasting or extrapolation” tool that incorporates outputs from descriptive analytics, machine learning (ML) algorithms, and simulation techniques to build accurate models that predict the future. Predictive analytics helps organisations capture changes in strategy over time and uses algorithms to predict outcomes (Labro, Lang and Omartian, 2023). As a result, decision automation becomes possible, providing management with the right tools to make sound recommendations for implementing future strategy.

Agri-food and beverage manufacturers can employ predictive analytics to optimise production capacity by predicting maintenance needs and reducing costs through improved anticipation of future demand, hence adjusting output and inventories accordingly (Sarker, 2021; Uche and Moyosore, 2025). The agri-food and beverage manufacturing industry operates under time constraints to ensure its products reach consumers while still fresh. Therefore, minimising equipment downtime is essential for success in this industry. The industry is being transformed by advanced analytics techniques like predictive analytics, which utilise data-driven insights to optimise production, reduce waste, and improve sustainability (Bastard and Chaillet, 2023).

3.3.4 Prescriptive Analytics

Prescriptive analytics recommends actions that can affect the outcomes generated from descriptive and predictive analytics. Appelbaum *et al.* (2017) suggest that prescriptive analytics go beyond descriptive and predictive by recommending one or more solutions and showing the likely outcome. Management may grasp the effects of the events of the preceding year and those that are forthcoming and develop a strategy based on this information. However without defining actionable steps, the efficacy of such a strategy cannot be guaranteed. The success of a business strategy thus depends much on prescriptive analytics, which provides information on what should be done (Sarker, 2021). Prescriptive analytics primarily involves suggesting conclusions or actions that can be taken based on data analysis. Chow-White and Green (2013) suggest that data collection, management, and analysis are communicative acts of decoding and encoding that transform and normalise complex activity and phenomena. This suggestion confirms that prescriptive analytics is the most valuable

of the four types of analytics, though it is also the most complex to implement (Jeyanthi *et al.*, 2022).

Through the insights gained from descriptive and predictive analytics, management accountants are equipped to employ prescriptive analytics, offering recommendations for optimal solutions and anticipated outcomes (Appelbaum, Kogan, Vasarhelyi *et al.*, 2017). They further clarify that although prescriptive analytics employs techniques and algorithms similar to those found in predictive analytics, it fundamentally seeks to evaluate the outcomes of these algorithms to identify the optimal solution. Hence, combining different analytics techniques can achieve extraordinary results. Appelbaum, Kogan and Vasarhelyi (2017) explain that prescriptive analytics seeks to optimise internal processes informed by descriptive and predictive analytics findings. For instance, in an organisation prioritising productivity, management accountants can use prescriptive analytics to identify the optimal solution, taking into account personnel competencies, transaction-processing intricacies, and output quality. For example, the agri-food and beverage manufacturing industry has developed operational systems that capture production floor activities in real time, making them intelligent systems for predictive and prescriptive analysis (Kilari, 2025).

3.3.5 Advanced and emerging types of analytics

The aforementioned analytical types may be utilised separately or in conjunction to extract optimal value from Big Data. In addition to the well-established four types of analytics that can be applied to big data, there are further advances and emerging analytics that are not standalone. Examples in the agri-food and beverage manufacturing industry include real-time analytics and cognitive analytics. They can enhance the main types of data analytics by providing up-to-the-minute data.

In the context of big data, velocity refers to the speed at which data is produced by devices (Rawat and Yadav, 2021; Ajax, 2025). Velocity refers to the rapid ingestion, storage, and processing of data in a dynamic data landscape. This extensive data can be processed either continuously in real-time or in batches, with real-time analytics being more relevant for big data. The ability to perform real-time text analysis enhances decision-making by providing up-to-the-minute information on customer

sentiments, market trends, and emerging issues (Abdullah and Mohammed, 2021; Ravichandran, Machireddy and Rachakatla, 2022). Real-time analytics applications include monitoring social media for complaints about product quality, analysing live customer interactions in a cognitive analytics tool such as chatbots, and extracting insights from real-time news feeds. In addition to real-time analytics, cognitive analytics uses AI or natural language processing (NLP) to simulate human reasoning (Ravichandran, Machireddy and Rachakatla, 2022; Ajax, 2025). To enhance supply chain and inventory management in the agri-food and beverage industry, AI-driven demand forecasting can use machine learning models to evaluate historical sales, weather events, and economic variables to produce more precise demand predictions (Kilari, 2025; Uche and Moyosore, 2025). The automation of manufacturing processes through robotics may be facilitated by AI, which will also benefit the agri-food and beverage industry.

It is worth noting that big data differs from BDA. Big data is about the raw data collected (Ajah and Friday Nweke, 2019), while BDA is the process of analysing the data to extract insights and facilitate decision-making (Kuo and Kusiak, 2019; Ciampi *et al.*, 2021). The integration of all data analytics techniques converts raw data into actionable insight, allowing organisations to comprehend, anticipate, and enhance outcomes (Y. Wang *et al.*, 2019). To optimise the advantages of data analytics techniques, businesses must evaluate the integration of diverse BDA strategies within their comprehensive business operations (Chatterjee *et al.*, 2023; Nneka Adaobi Ochuba *et al.*, 2024).

3.3.6 Section Summary

Although the vast majority of data analytics efforts are devoted to descriptive analytics (what happened) and predictive analytics (what could happen) (Lepeniotti *et al.*, 2020), prescriptive analytics (what should be done) is becoming increasingly relevant as organisations seek a competitive advantage. Meanwhile, prescriptive analytics is seen as a source of recommendations for actions that can affect future outcomes (Sarker, 2021; Jeyanthi *et al.*, 2022). Various analytical techniques are applied at different levels, combined with improved MCS. Numerous difficulties confronting the agrifood and beverage industry will need the utilisation of advanced analytics, such as

prescriptive and predictive analytics (Sharma *et al.*, 2021). For example, prescriptive analytics can enhance supply chain management systems by optimising inventory management (e.g., EOQ), route selection, and supplier selection. Predictive analytics can enhance predictive maintenance by advising on optimal servicing times for equipment before problems arise.

Data analytics is pivotal because it directly relates to the company's decision-making processes, potentially transforming how the organisation functions (Merendino *et al.*, 2018). One of the most significant issues identified in the literature is how this transformation in organisational function translates into business value to organisations (Côrte-Real, Oliveira and Ruivo, 2017; Vidgen, Shaw and Grant, 2017; Grover *et al.*, 2018; Richards *et al.*, 2019; Lepenioti *et al.*, 2020; Silva *et al.*, 2021; Chandra Panda and Agrawal, 2024; Wissuchek and Zschech, 2024). The analysis gap becomes wider when the concept of simplicity versus complexity is considered, as pointed out by Al-Htaybat and von Alberti-Alhtaybat (2017). The impact of BDA techniques on MCS is dependent on the MCS strategies in operation within the organisation. Data analytics can reshape how a company operates, but the value it creates depends on balancing simple and complex analytical systems and ensuring they align with existing management control practices. It is therefore crucial to establish how BDA facilitates a holistic perspective on MCS, which incorporates the LOC and the complex organisational context. The following section reviews key MCS themes that are likely to benefit from the use of BDA.

3.4 Common BDA themes:

Some authors have used the terms 'big data,' 'business intelligence,' and 'business analytics' interchangeably, making it difficult to find a unique definition for each of them separately. This study focuses on the BDA as defined in Section 2.2 to establish its relevance to MCS. In this regard, several common themes have emerged in the literature on the relevance of BDA to MCS implementation. Although most publications on BDA have focused broadly on its potential impact on decision-making and value creation, some have provided guidelines on barriers to the successful use of BDA to aid in the implementation of MCS.

3.4.1 Application of BDA in Decision-making

As we enter the fifth industrial revolution, businesses across industries face everincreasing disruption and opportunities created by the growing volume of data. Datadriven decision-making is a method for determining a course of action based on highquality data systematically used in intelligence to assess, test, and improve business processes. BDA provides excellent resources and a robust methodology to support the data-driven decision-making process (Liang and Liu, 2018). Data-driven decisionmaking involves providing the correct data to the right people at the right time to solve problems and improve performance effectively (Tsaniyah *et al.*, 2025). The more organisations characterised themselves as data-driven, the better they performed on objective measures of financial and operational results; hence, data-driven decisions tend to be better (McAfee and Brynjolfsson, 2012; Y. Wang *et al.*, 2019; Wang *et al.*, 2022). As data-driven strategies take hold, they will become an increasingly important point of competitive differentiation (Barton and Court, 2012; Singh *et al.*, 2023). Decision-makers increasingly rely on the successful supply of relevant and accurate data, making BDA more relevant in a modern business environment. It is axiomatic that if a BDA system exists to support decision-making in an organisation, then the BDA developers need to understand the organisation's decision tasks and work with decision-makers to improve the effectiveness of their decision-making (Arnott, Lizama and Song, 2017). This rule also holds for decision-makers, who should be data-centric and technologically aware of the available BDA tools. Although attention to technology is insufficient, it remains a necessary component of a big data strategy (McAfee and Brynjolfsson, 2012), and decision-makers need not be experts in BDA systems (Dehkhodaei *et al.*, 2023).

Information must be structured so that managers can interpret and act on it immediately. Within Simons' *Levers of Control* framework, this requires information systems that support diagnostic, boundary, and interactive controls (Simons, 1995). Diagnostic controls rely on well-designed dashboards that foreground critical performance variables such as line-level throughput, equipment-specific OEE, batch-yield variance, or real-time temperature and humidity readings, enabling agrifood and beverage companies to monitor operations efficiently and detect deviations from expected performance (Bedford, 2015; Arnott, Lizama and Song, 2017; Liang and Liu, 2018). Boundary controls are reinforced through algorithmic forecasting tools that

identify emerging risks, for example, predicting microbial contamination, allergen-cross-contact, or ingredient-quality deterioration due to supply chain disruptions. Advances in machine learning and predictive analytics strengthen these boundary systems by improving the accuracy of risk detection and enabling earlier intervention (McAfee and Brynjolfsson, 2012; Y. Wang *et al.*, 2019; Wang *et al.*, 2022; Singh *et al.*, 2023).

Real-time data increasingly enhances interactive control processes by enabling more frequent, informed dialogue about strategic uncertainties (Mundy, 2010). Continuous data streams from IoT-enabled production lines, automated quality-inspection systems, or smart packaging technologies support ongoing conversations about fluctuating demand, shifts in raw-material characteristics, or progress toward energyefficiency targets. Such real-time insights transform interactive controls into dynamic mechanisms for organisational learning and strategic adaptation (Henri, 2006; Dehkhodaei *et al.*, 2023; Tsaniyah *et al.*, 2025). Together, these information practices ensure that decision-makers receive timely, actionable insights that reinforce all four levers of control in a sector characterised by stringent regulation, biological variability, and volatile consumer preferences.

3.4.2 BDA Techniques and Value Creation

Although the last ten years have witnessed a surge in research on big data and business intelligence, limited attention has been paid to harnessing big data to improve managerial and economic decisions (Sheng, Amankwah-Amoah and Wang, 2019; Sardi *et al.*, 2023). Most research has focused on technical issues like data mining, warehousing, analysis and visualisation techniques (Cuthbert and Pearse, 2022; Alsolbi *et al.*, 2023; Attar-Khorasani and Chalmeta, 2024). The agri-food and beverage industry considers the extensive data generated by IoT highly valuable, and data mining methods can be used to uncover hidden insights within it. In the BDA landscape, managers must determine whether data is essential and beneficial, as the value of data is contingent upon its application (Daskalova and Ivanova, 2021). Overall, when utilised effectively by data scientists, BDA techniques can reveal organisational value and enhance revenue and profitability through the identification, analysis, and strategic implementation of patterns (Cuthbert and Pearse, 2022). Although big data research has seen rapid growth in management disciplines, it is still

in its early stages, and many key questions remain unanswered (Sheng, AmankwahAmoah and Wang, 2019).

BDA investments, like any technological investment, should generate tangible business value (higher profits, greater innovation, or improved resilience) rather than simply addressing a technological need. (Grover *et al.*, 2018; Magableh, Kannan and Hmoud, 2024; Dzreke and Dzreke, 2025). There is an ongoing need to evaluate how effectively BDA supports MCS, particularly in the agri-food and beverage industry, where control systems tend to be especially complex (Chapter 2). Key issues that determine how organisations draw benefits from big data include organisational capabilities (BDA skills), organisational culture (signification, domination and legitimisation), risk management (privacy, bias, surveillance, and over-reliance on algorithms) and organisational context (industry, size, demographics and location) (Conrad, 2014; Feeney and Pierce, 2016; Rodríguez-Espíndola *et al.*, 2022; Horvey *et al.*, 2024). Understanding how these nuances are navigated to ensure the successful use of BDA in facilitating MCS is among the objectives of this study.

3.4.3 Barriers to the strategic application of BDA in MCS implementation

Although considerable evidence attests to the benefits of BDA for MCS (Griffin and Wright, 2015; Vasarhelyi, Kogan and Tuttle, 2015; Murthy and Geerts, 2017; Rikhardsson and Yigitbasioglu, 2018), there remains insufficient clarity about which advanced techniques have been developed. These benefits include improved planning, performance measurement, and risk control in this industry. For example, real-time visibility into production efficiency (line speed, downtime, yields), tighter control over quality and food safety (temperature logs, HACCP checks, traceability), and improved cost control and margins (better demand forecasts, waste tracking, promote effectiveness). Despite the perceived benefits, companies in the agri-food industry have yet to clearly demonstrate how they benefit from advanced analytics. For example, companies frequently refer to “AI,” “machine learning,” or “advanced analytics,” yet it is often unclear whether they are relying on basic tools such as dashboards and simple regressions or employing techniques, such as deep-learning models for visual tasks or reinforcement-learning systems for scheduling (Arrighi *et al.*, 2025; Siddique *et al.*, 2025). In the context of food and beverage firms, this

ambiguity poses challenges because although BDA can enhance MCS, the underlying control logic and governance structures surrounding these tools are often insufficiently defined. A better understanding of how BDA facilitates MCS can resolve common issues like (Yadav *et al.*, 2022; Contuzzi, Galiano and Casalino, 2025):

- challenges in designing KPIs and control processes around analytics that users don't fully understand (for example, how to review an IOT report that flags quality issues).
- Difficulties in comparing manufacturing units (cost centres) or product range if each uses different, poorly documented "advanced" tools.
- Managers may either place too much confidence in the analytics or dismiss them prematurely because they lack insight into how robust, transparent, or reliable the underlying models actually are.

BDA is increasingly enabling the agri-food and beverage industry to manage costs, quality, and risk more effectively. However, the field still lacks a systematic understanding of which advanced analytical techniques are actually being developed and embedded within formal MCS. In addition, challenges arise both from the inherent characteristics of BDA and from how these tools have been applied in practice and conceptualised in scholarly research (Sheng, Amankwah-Amoah and Wang, 2019). The technical complexity, opacity, and rapid evolution of BDA pose challenges for organisations seeking to integrate these tools into existing structures. At the same time, academic discussions often treat BDA in broad or inconsistent terms, contributing to ambiguity about its capabilities, limitations, and implications for management control. Though greater efficiency is a primary goal in handling such data sets, the very nature of big data (the 6Vs) presents challenges (Sinaeepourfard *et al.*, 2015; Sivarajah *et al.*, 2017). As businesses become increasingly reliant on big data, ERP solution providers have sought to integrate legacy systems with big data to ensure their solutions can effectively handle data from various sources. For example, technological advancements in cloud computing, big data systems, No-SQL databases, cognitive systems, deep learning, and other artificial intelligence techniques make the integration of traditional ERP transaction data and big data streaming from various social media platforms and the Internet of Things (IoT) into a unified analytics system not only feasible but also inevitable (Shi and Wang, 2018). As ERP implementers and BDA users face various challenges, managers responsible for this big-data ERP-BDA integration are also under significant pressure. To help them deal with these

challenges, Shi and Wang (2018) propose the SIST model. They proposed that this integration is an evolving portfolio with varying levels of maturity across different business functions, likely to lead to sustainable competitive advantage. The SIST model includes Strategic alignment, Intellectual and Social capital integration, and Technology integration.

Management information systems have traditionally produced information for decisions that fairly demarcate long versus short-term implications (Aina, Hu and Mohammed, 2016). With the introduction of big data, such clarity of differentiation may no longer apply, as big data collection focuses on aggregating large numbers of ongoing digital activities and, therefore, is operational. Strategic visions derived from this data will inevitably extend the implications of aggregated operational information content to longer-term planning decisions, reducing clarity regarding both the short and long term (Bhimani, 2015). Therefore, data-centric decision-makers may apply in-depth judgment to assessing information acquired from big data, making the decision-making process more subjective (Ranjan and Foropon, 2021; Oesterreich, Anton and Teuteberg, 2022; Tenali and Babu, 2023).

There is consensus among academics and practitioners that the primary goal of BDA is to create a suitable context in which organisations can respond appropriately to a changing environment. BDA has facilitated how organisations manage their businesses, allowing them to access timely and relevant data by integrating structured and unstructured information and aiding decision-making (Ashrafi *et al.*, 2019). Data collection, management, and analysis are communicative acts of decoding and encoding that transform and normalise complex activity and phenomena (Chow-White and Green, 2013). The nature of big data poses technical challenges for data management and analytics. Still, applying advanced technologies and techniques at each stage of the analytics workflow makes big data manageable, enabling the extraction of valuable information to inform business decisions. Management must consider three key components responsible for an ICT system's success in creating business value from BDA investment. These issues can be summarised into technical and human capabilities.

Technical issues

Businesses will need the tools and skills to extract valuable data from the abundant supply, posing another challenge as they struggle to maintain a competitive advantage. In the past, management has preponderantly acquired data manually at the initiation of transactions, the core of which was traditional data and typically incorporated legacy and ERP data (Vasarhelyi, Kogan and Tuttle, 2015). With technological advances, data comes from various sources like website logs, social media, sensor logs, communication repositories, and intranet/extranet logs (Patil, Karnik and Sawant, 2015; Abourezq and Idrissi, 2016; Murthy and Geerts, 2017; Srivastava and Jaiswal, 2019; Anayo Chukwu Ikegwu, Henry Friday Nweke, Chioma Virginia Anikwe, 2022; Dara Sawitri, 2024).

The effectiveness of the BDA system depends on the information being fed into the system. This challenge is further exacerbated by the difficulties in extracting, storing, and analysing all the information generated by the ever-growing volume of data. Big data technologies facilitate data collection, analysis and information delivery. They are designed to support decision-making (Rikhardsson and Yigitbasioglu, 2018), but in line with most innovative technologies, there are a series of technical challenges to their successful implementation.

It is possible to recognise intricate patterns within the data using data-driven methodologies, such as data mining. Data mining algorithms serve as the principal models and instruments for knowledge discovery (Kuo and Kusiak, 2019). Fayyad (1996) defined data mining as the nontrivial process of identifying valid, novel, potentially practical, and ultimately understandable patterns in structured databases. Data mining primarily discovers patterns in large datasets and involves various methods from disciplines such as machine learning, statistics, and database systems. In terms of barriers to implementing the data mining solution, the primary sources of difficulty are the complexity of the overall organisation and the incompatibility among the multiple data feeds from various applications into a centralised system (Sena *et al.*, 2019).

Following the extraction of relevant data, it must be transformed into information useful for decision-making. Sometimes, the decision-maker is given more information than they need for the situation, necessitating further analysis. The phenomenon is generally known as information overload, which presents numerous challenges and is further exacerbated when reports are poorly designed in how information is presented, often distracting decision-makers' attention (Yigitbasioglu and Velcu, 2012). Therefore, BDA technology must utilise effective visualisation techniques to guarantee that only pertinent and suitable information is conveyed to the decisionmaker. These technical issues require skilled personnel to address them. With the adoption of cloud-based BDA, compliance and security risks are becoming even more prominent as additional vulnerabilities are introduced with the changing location of the data, thus requiring personnel management to increase awareness of data-related issues and employee training (Rikhardsson and Yigitbasioglu, 2018).

Human Capabilities

The mediation of human relations by communication technologies lies at the core of the communication process, from language to print, radio, film, television, internet, new media, and now algorithmic culture and data mining (Chow-White and Green, 2013). In the same way, humans are at the core of the success of any MCS (Janke, Mahlendorf and Weber, 2014; Cugueró-Escofet and Rosanas, 2015); they also influence the success of the BDA system (Yigitbasioglu and Velcu, 2012). Technology has made it easy to measure, design systems, and produce information (e.g., reports) to facilitate decision-making. Still, the success of the decision-making process depends on the end user's ability to extract data from the system in a meaningful and helpful way (Rikhardsson and Yigitbasioglu, 2018). The emergence of Human-Computer Interaction (HCI) was driven by the shortcomings of existing approaches to adequately describe and understand how people interact with a new breed of pervasive digital technologies in everyday life (Frauenberger et al., 2016). Hence, a successful BDA project requires personnel or a team with skills that many human resource experts report as in short supply (World Economic Forum, 2023).

Organisations are more likely to develop enterprise-wide data warehouses if the BDA application focuses on creating consistency or transformation rather than generating

insight. The latter goal might present challenges from a data quality point of view, as data would be more comprehensive, less structured, and potentially in real-time (Rikhardsson and Yigitbasioglu, 2018). Therefore, the approaches to data collection in organisations will depend on the overall purpose of the BDA application (gaining insights, achieving consistency or fostering transformation). A typical BDA system should link ICT experts, business experts and end-users (Brichni *et al.*, 2017). It requires a broad knowledge-management system, which is difficult to build and keep secure for everyone's needs in the organisation. Some of the above challenges may be more prominent in some industries than others.

3.5 Conclusion

The attempt to define the attributes of big data clarifies the diverse data sources that might otherwise have been overlooked. Understanding the various data analytics methodologies applicable to big data is crucial for comprehensive information extraction. Advanced analytics, including real-time and cognitive analytics, can benefit agri-food and beverage manufacturing companies in various ways, such as enabling predictive maintenance and ensuring regulatory compliance through prescriptive analytics. The choice of BDA techniques must match the organisational strategies to maintain a competitive advantage. Important BDA outputs, including information for decision-making and value creation, are crucial in evaluating the success of BDA usage. The influence of BDA on company performance (Tambe, 2014) and how management capabilities impact the success of BDA (Brynjolfsson, Hitt and Kim, 2011) have been studied, but limited studies have investigated the simultaneous quantifiable impact of both components (technical issues and management capabilities) (Müller, Fay and vom Brocke, 2018).

Big data capabilities have ushered in a new era for agri-food and beverage manufacturing companies, enabling executives, production managers, process engineers, and procurement managers to make more informed decisions. The efficient application of BDA will result in leaner production operations and can help organisations become more profitable and maintain a competitive advantage. Because BDA systems are complex and must align with existing MCS practices (Vitale, Cupertino and Riccaboni, 2020; Solano and Cruz, 2024), the study adopts a theoretical

framework that accounts for this complexity by explaining how BDA interacts with organisational routines, decision-making structures, and control mechanisms. This allows the study to examine not just whether BDA tools are used, but how they fit or do not fit within established control logics, how they reshape information flows and decision rights, and how they influence the balance between diagnostic, interactive, boundary, and belief systems. SST offers a suitable framework for analysing complex relationships by examining how agents understand and respond to external structures and other actors in their context (Conrad, 2005; Englund and Gerdin, 2014; Feeney and Pierce, 2016, 2018). By grounding the analysis in a framework that recognises these interdependencies, the study can better capture the organisational conditions under which analytics generate value, create tensions, or require adjustments to existing control designs (Smith and Lewis, 2011; Carhart and Rosenberg, 2016; Feeney and Pierce, 2016).

Chapter 4 Research Framework—Strong Structuration Theory (SST)

4.1 Introduction

Qualitative research can be inductive (generating new theories) or deductive (testing existing theories). However, even in inductive approaches, a framework provides a starting point and helps researchers make sense of their discoveries. SST constitutes a theoretically robust and empirically applicable framework that foregrounds the dynamic interplay between structural conditions and human agency within situated social contexts (Stones, 2015). SST provides a practical framework for analysing how structure and human agency interact within specific contexts. SST allows for a detailed investigation into the enabling and constraining features of the BDA and MCS structures that impact the day-to-day management of resources, providing a comprehensive framework for empirical analysis in this field (Englund and Gerdin, 2011). The remainder of this chapter elaborates on the relevance of SST in accounting research and its rationale as an analytical framework for studying the BDA-MCS relationship. Finally, the chapter explains how the researcher employed SST for data analysis. This thesis focuses on the agri-food and beverage industry, and therefore examples from this industry will be used to contextualise SST where appropriate.

4.2 Relevance of Strong Structuration Theory in Research

Following the initial publication of the structuration theory (Giddens, 1984), there have been ongoing debates regarding its application to management research. Giddens' (1984) fundamental idea of the duality of structure suggests that structures (the enduring patterns and institutions of society, like laws and resources) and agency (the capacity of individuals to act independently) are mutually constitutive, hence enhancing the clarity of empirical analysis (Stones and Jack, 2016; Jack, Florez-Lopez and Ramon-Jeronimo, 2018). Structures are the enduring patterns and institutions of society (like laws and resources), while agency is the capacity of individuals to act independently. The debate has centred around the fundamental tenet of the 'duality of structure,' which Giddens argues should be understood as a set of social rules and resources that influence actions and outcomes. The duality of structure is a key concept in structuration theory that posits that social structures are both the medium and the outcome of human action (Stones, 2015; Feeney and Pierce, 2016; Kennedy,

O’Gorman and Lee, 2021; Stirk, 2021). This notion implies that individuals and groups shape and create social structures through their actions, while these structures also constrain and enable future actions.

Giddens emphasises the duality of structure, but Stones (2005) contends that Giddens’s neglect of the relationship between agents, structures, and external pressures limits the concept’s applicability to empirical research. Giddens’ integration of structure and agency into a dynamic process known as the "duality of structure" complicates its application in empirical research because the term “structure” is abstract, leading to ambiguity in measurement. Social structures make human action possible, but such action sustains or alters the social structure itself (Giddens, 1984). In other words, social structures dictate human actions, but human actions also influence these social structures. Therefore, the theory suggests an inherent interdependence between societal structures and human agency. For example, the successful implementation of a strategy is guided by its content and individuals’ ability to execute it.

Giddens’ simplistic approach to the concept of “duality of structure” has led some researchers, such as Archer (1995), to argue that Giddens underestimates the restricting strength of institutions, making it challenging to explain why some social patterns persist despite human resistance. Although the duality of structure remains the foundation for analysing data in situations involving human actions influenced by social structures, Archer (1995) agrees that social theory must explain the relationship between individual agency and social structure. She admits that the pre-existence of social structures (such as institutions and norms) and cultural systems (such as beliefs and values) shapes the contexts in which agents operate. Also, in agreement with Giddens, these pre-existing social contexts are not deterministic; instead, they provide constraints and opportunities for enablement. In contrast to Giddens’ structuration theory, which posits a simple bi-directional relationship between structure and agency, Archer (1995) considers them as separate yet interrelated entities in a web-like relationship. She suggests a morphogenetic approach as a fundamental framework in interpretivist social theory, offering a dynamic model to explain how social structures and human agency interact to produce change over time. This facilitates the analysis of how structures precede actions and how agency can modify them, hence dualism.

Meanwhile, social properties may arise from norms and institutions, yet cannot be reduced to the individual actions of agents with autonomous causal powers (Archer, 1995). Stones addresses these weaknesses by developing "strong structuration theory", which elucidates the dimensions of the duality of structure, which he categorises as signification, domination and legitimation.

Stones (2005) suggests a reinforced ontology that incorporates the true nature of reality and allows substantive empirical research to be developed using the theory, a suggestion warmly embraced by Jack and Kholeif (2007). They further echo Stones' (2005) argument that structure and action are not contemplated in the abstract but observed in concrete situations through the how, why, where and what of everyday occurrences. This observation is achieved through understanding the dispositions and practices of agents. Giddens' structuration theory is a comprehensive ontology that elucidates the abstract interrelation between structure and agency, positing a duality in which each is contingent on the existence of the other. Stones depicts this ontological approach as ontology-in-general due to its flat nature. In contrast, Stones presents an advanced version of structuration theory that preserves the duality of structure, which incorporates a keen focus on ontology-in-situ, addressing social processes and events at specific times and locations to mitigate the excessively abstract and philosophical aspects of Giddens' work (Jack, 2017). This evolution from 'ontology-in-general' to 'ontology-in-situ' is the cardinal point of Stones (2005). Stones' SST framework represents an ontologically distinct version of structuration theory, where Stones gives greater prominence to spatial relations and how different actors interact with one another, identifying a sliding scale of ontological abstraction and offering the potential for multi-layered studies of sociological phenomena (Coad, Jack and Kholeif, 2016). SST enhances Giddens' original structuration theory by proposing a quadripartite framework for examining the interplay between structure and agency in empirical research.

The quadripartite framework analytically distinguished four separate but interlinked aspects of the duality of structure (Stones, 2005: 75), with the last three being reformulations of Giddens' structures of signification, legitimation and domination (pp. 17-20). Stones' framework did not reject the duality of structure; rather, it

expanded it into four analytically distinct components, resulting in the quadripartite cycle of structuration (Coad, Jack and Kholeif, 2016; Feeney and Pierce, 2016). The quadripartite cycle of structuration is a model that describes the ongoing process of structuration in social systems, involving the interplay between four key elements: the external structures, the internal structures, active agency and outcomes (Stones, 2005: 75). As individuals and groups act within the social system, they are simultaneously shaping and creating the structure of that system, which in turn constrains and enables future actions (Stones, 2005). By focusing on a single cluster of agents (for example, an individual, a team, or an organisation), the networks of relationships, norms, sanctions, knowledgeability, and power resources within which this agent-in-focus operates can be mapped and evaluated (Jack and Kholeif, 2007). This study analyses the external structures by referencing the boundaries drawn by the agent-in-focus between the internal and external structures. *Figure 8* shows the interconnections among the components of the quadripartite cycle of structuration.

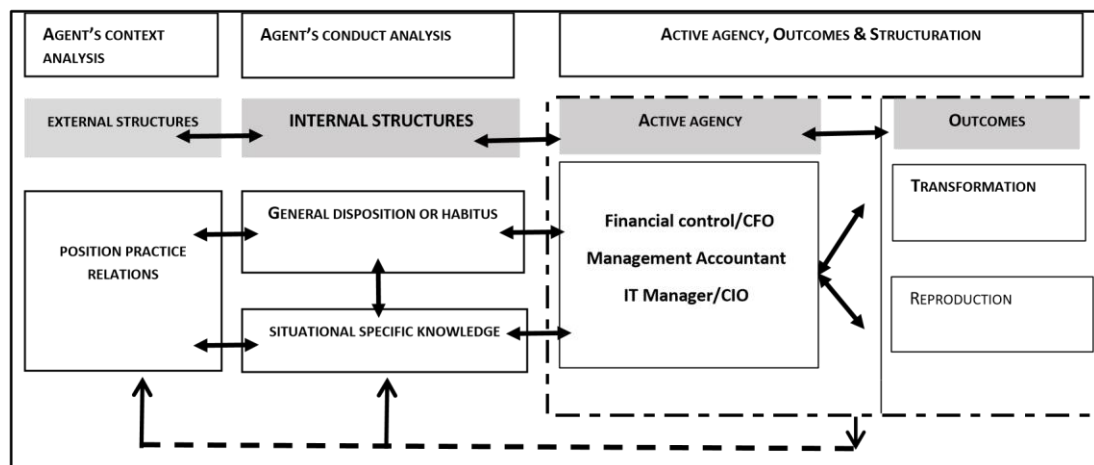


Figure 8: The quadripartite nature of structuration [Source: adapted from Stones (2005: 85)]

Agent's context analysis

Structure refers to the rules, norms, and resources that shape social interactions and guide individual behaviour (Bodolica, Spraggon and Tofan, 2016). These include formal institutions, cultural values, and social expectations, which permeate the hierarchy of positions, decision-making processes, and communication channels. Stones (2005) describes external structures as conditions for action, which include preexisting social, cultural, and institutional constraints/enablers that shape agents' possibilities. External structures comprise both acknowledged and unacknowledged conditions of action, which may serve as the foundation for unintended consequences;

these factors can either constrain or facilitate the actions of an agent-in-focus (Jack and Kholeif, 2007). Stones (2005) suggests that external structures may exert some influence on internal structures and agents, which may be independently causal or irresistible.

Technology is considered one of the biggest influencers, given its presence in the physical tools and machinery used in the manufacturing process. Agents rely on technology (structure) to perform actions geared at achieving desired results (outcomes). The type of technology used can influence the organisation's structure and the culture of its workers. For example, introducing automated machines in a factory can change how work is organised and the skills needed by workers. Technology can be viewed as the external structure when analysing the agent's context, in that a software package's specifications influence how data is collected and utilised in agrifood and beverage manufacturing. Therefore, the agent depends on technology to perform their job successfully, as depicted by Stones (2005) as a position practice relation.

The internal structures

Internal structures can also be analysed in terms of the agent's situational knowledge of external structures and its general disposition. Situational knowledge refers to the idea that social structures are pre-determined, but are not fixed and are continually created and recreated through the actions of individuals and groups (Stones, 2015). Individuals have agency within the limits set by social structures. These limits are not fixed but constantly change, depending on the conjunctural factors affecting society at any given time.

Meanwhile, Giddens' (1974) general disposition, or Bourdieu's (1977) habitus, refers to the socially constructed and internalised dispositions, tendencies, and behaviours that individuals develop due to socialisation and interaction within a given social structure. Stones (2015: 88) describes habitus as "the ingrained, durable, cultural and value dimensions of a person's habitus are an important key to understanding the perspective from which that person will view a particular situation". These dispositions are not fixed but are dynamic and constantly evolving through social

interactions and practices. For example, acquiring a bespoke software package versus buying an off-the-shelf (OTS) version may be influenced by users' general dispositions or habitus (habits or skills). However, the acquisition of a bespoke software package without the right skills to operate it will be considered a waste of resources. Therefore, management's decision to acquire bespoke software is driven by multiple factors, some strategic (fixed) and others not (variable).

On the other hand, skilled individuals (active agents) might bring out the best in an OTS package, making it more valuable than a bespoke package. Stones (2005) describes Active Agency as the agent's routine, pre-reflective, and strategic and critical, drawing upon her internal structures to influence outcomes. The system user may or may not follow the system's operation guidelines, which would affect the outcomes. The effect of agents' practices on extant structures can involve change, elaboration, reproduction, and preservation (Stones, 2005). Change is not usually accepted easily and can significantly influence outcomes. A typical information technology system cycle includes input, processing, and output. Input depends mainly on users' knowledge of the system, though most systems have error-prevention coding built in to prevent incorrect data from entering the system. Therefore, a combination of external and internal structures, as defined by Stones (2005), should ensure successful input. However, the system's processing capabilities are tied to the external structures, which should be considered throughout the system development life cycle (SDLC) in tandem with business processes.

Researchers are moving forward from a rigid application of the quadripartite framework to a more dynamic approach that incorporates additional essential components of SST, emphasising the concept of agency-in-situ rather than solely on structure, disconnected from agency (Coad, Jack and Kholeif, 2016). As Coad et al. (2016) put simply, researchers are more interested in people (individually or collectively) and their analysis of conduct and context using SST. The SST model developed by Stones (2005) is considered an excellent fit for multiple case study research in accounting, organisation and management (Jack and Kholeif, 2007; Coad et al., 2016).

4.3 Strong Structuration Theory as a Theoretical Framework for Studying the BDA-MCS Relationship

SST provides the researcher with a tool to take a broad view of implementing BDA-enabled MCS and the individuals involved in its implementation within a given organisational setting. The framework aims to support researchers in deepening their understanding of how social norms, rules, and agencies influence organisational controls, while also assisting managers in balancing formal controls with employees' adaptive behaviours. Most accounting systems are designed primarily to produce information for statutory reporting (Ramli and Iskandar, 2014). Still, it can be argued that the information generated by the system could also be used for purposes other than statutory reporting. This argument is more relevant in today's business world, given the increased availability of data. A typical accounting system is produced by identifying the relationship between the system and the business processes (Trigo, Belfo and Estébanez, 2016). The design and implementation of accounting systems are intended to address current and forecasted business processes, but they also resolve issues that were not planned. Therefore, a more concise framework is required when examining the effective use of accounting systems.

Two significant factors influence the outcomes of business processes: (1) the system designed to ensure the successful implementation of the business process and (2) the knowledge of those charged with implementing the system. These mediating factors fit perfectly into Giddens' (1984) theory of duality of structure, with the system considered part of the external structure, while those responsible for the implementation represent the agent. Stones (2005) further analysed the agent in terms of internal structures and active agency (agent's practices). This research draws on the active agent to explore the factors influencing its successful use of BDA in controlling the execution of essential business processes. In this regard, business processes, however well planned (for example, correctly linked to organisational strategy), may not succeed if any party involved in their execution is misrepresented (or missing).

Successful use of complex technology like BDA depends on the resources available, the capabilities of those charged with its implementation, and the influence of organisational structures. Although attention to technology is insufficient, it is always

a necessary component of a big data strategy (McAfee and Brynjolfsson, 2012), and decision-makers do not need to be experts in BDA systems (Dehkhodaei et al., 2023). Stones' SST has been adopted as an analytical framework for similar studies due to its demonstrated capacity to account for the interaction between agency and social structures in the production, reproduction, and regulation of social order, as well as its potential to analyse organisational change (Conrad, 2005). As Feeney and Pierce (2016) point out, this theory primarily concerns itself with understanding the relationships between the activities of knowledgeable agents and the structuring of social systems. In hindsight, SST is considered more suitable for this study, as it presents a lens through which the researcher would gain deeper insights into 'how' BDA influences and is influenced by MCS. Empirically, developing the "sliding scale" as a mechanism for contextualising research, SST enables researchers to position their studies on a scale from in-depth individual investigations to the more abstract contemplation of global phenomena (Jack and Kholeif, 2007). This study leans towards the latter as it seeks to identify the impact of BDA on MCS, which may include non-linear change and unintended outcomes.

The use of BDA-enabled MCS is influenced by various factors, which can be grouped into two main categories: the system (MCS) and the technology (BDA) used to implement it. Building on Giddens's duality of structure, the system dictates what data must be collected, while the available technologies influence how systems are designed. Undoubtedly, advances in technology have influenced the strategies of the agri-food and beverage industry (similar to other process-intensive manufacturing industries). Similarly, software vendors continually develop applications that address the strategic needs of the industry. Meanwhile, the strategic needs of a company are influenced by many factors, including the organisational culture. Culture refers to the organisation's shared values, beliefs, and norms. These include attitudes towards work, relationships between workers, and expectations placed on individuals. Culture can influence how an organisation is structured, the technology used, and the actions taken by its individuals. Therefore, the actions taken by individuals collectively or alone (agency) are influenced by many factors, some of which are beyond the control of the individual(s). Hence, the web-like connection of the various components of the quadripartite nature of structuration, with the agent being at the centre of it all. Agency

refers to the individual actions and choices of the workers within the organisation. Individuals can act within or against the existing structures, culture, and technology. For example, workers may adopt new technology, challenge the existing structure, or resist the organisation's culture.

4.3.1 Rationale for using SST as an analytical framework

The four components of the quadripartite nature of structuration are mutually constitutive, meaning that each one influences and is influenced by the others (Coad and Herbert, 2009; Englund and Gerdin, 2011; Kennedy, O’Gorman and Lee, 2021). Changes in one component can lead to changes in the others, creating a cycle of structuration. For example, introducing new technology can lead to changes in the organisation's structure, which can affect workers' culture and, consequently, the actions taken by individuals. Similarly, changes in individual actions can lead to changes in the technology used, the organisation's structure, and the workers' culture. SST is a theoretical framework that suggests that social structures are not just external constraints on individuals but are also internalised and reproduced through their actions (Bourdieu, 1977; Giddens, 1984; Stones, 2015; Coad, Jack and Kholeif, 2016; Kennedy, O’Gorman and Lee, 2021; Loughmiller-Cardinal and Cardinal, 2023). In analysing qualitative data on BDA in the agri-food and beverage industry, SST can be used to understand how BDA practices are shaped by both the industry's external structures and the individuals' internalised structures. This analysis can help researchers to understand how the structures and agency of the individuals and organisations involved shape the industry (Eteläpelto *et al.*, 2013; Ruth Eikhof, 2017; Galleli and Amaral, 2025).

While building on the quadripartite cycle of structuration, four integrated steps can be followed to analyse qualitative data:

1. Agent's context analysis: The external structures that shape data analytics practices in the agri-food and beverage industry might include government regulations, industry standards, market demands and technological advancements. This study focuses on technological advancements, aiming to investigate how BDA influences MCS in the agri-food and beverage industry and how the industry, in turn, impacts BDA requirements. Stones conceptualise

these structures as clusters of practices, as part of the agent's context analysis (Figure 8)

2. Agent's conduct analysis: Next, identify the internalised structures that influence how individuals within the industry engage with data analytics. These structures might include organisational culture, personal beliefs, values, and professional norms. Stones (2005) describes these individuals as the relevant agents (individuals or groups) that carry out social action. In the agrifood and beverage industry, relevant stakeholders include those responsible for managing agri-food and beverage companies, government regulators, and consumers. The actions of agents (agents' conduct) depend on other factors, like power dynamics that define what they can or cannot do with the resources at their disposal. Agent's conduct analysis involves systematically assessing an agent's behaviour, decision-making, and performance within the framework (Stones and Jack, 2016). This study helps uncover the strengths, shortcomings, and areas for performance improvement of agents. Agent conduct analysis examines how an in-situ actor (agent) interprets the context in connection to their values, duties, obligations, and worldview, resulting in their actions (Stones and Jack, 2016).
3. Active agency: At this step, the researcher analyses the interplay between external and internalised structures and how the agent makes use of them to influence outcomes. The active agency seeks to demonstrate how the SST framework is utilised to explain the interaction between external and internalised structures that shape data analytics practices within the industry. One of the key tenets of SST is that structures and agency are mutually constitutive (Jones and Karsten, 2008). Analysing the relevant structures and agents that interact to produce social action within the agri-food and beverage industry helps explain how BDA is currently used to facilitate MCS. For example, the products manufactured may influence the types of data collected and analysed, while organisational culture may influence how employees use that data.

4. Outcomes: Finally, the analysis identifies opportunities for change, especially within the industry. For example, if the analysis identifies that a particular organisational culture hinders effective data analytics practices, it will recommend changes to that culture to improve outcomes. Meanwhile, if the outcomes are deemed beneficial to the company, employees would be encouraged to maintain the *modus operandi*. Consequently, outcomes may be either reproductive or transformative of a particular strategy.

These four steps are based on Stones' quadripartite cycle of structuration, which generates a web-like analytical framework (Figure 8), depending on the researcher's starting point and the research question.

4.3.2 Strong Structuration Theory: Methodological Bracketing

Methodological bracketing involves using the analytical distinctions outlined above to examine and understand the interplay between the company's structures and the actions of its employees or institutions. By breaking down the analysis into specific components, researchers can understand how various elements within the company influence and are influenced by individuals' and groups' behaviours. According to Stones' SST, the impact of internal structures on outward structures is not onedirectional; rather, it is part of a continuous, recursive process (Conrad, 2005; Kennedy, O'Gorman and Lee, 2021). Across all industries, the way companies operate internally is constantly being influenced by and also affects the rules and expectations set by external forces, such as government regulations and societal expectations. This dynamic interaction emphasises the significance of understanding how organisational agency within companies can drive broader structural transformations in the industry. For example, when new regulations are introduced in the agri-food and beverage industry, companies may be required to modify their production processes to comply. This scenario illustrates how external forces impact internal practices. The reverse could occur when a company develops an innovative food packaging technology, prompting regulatory bodies to modify industry standards.

Using SST to analyse qualitative data can provide a comprehensive framework for understanding the complex interplay between external and internalised structures and identify opportunities for change to improve data analytics practices within industry.

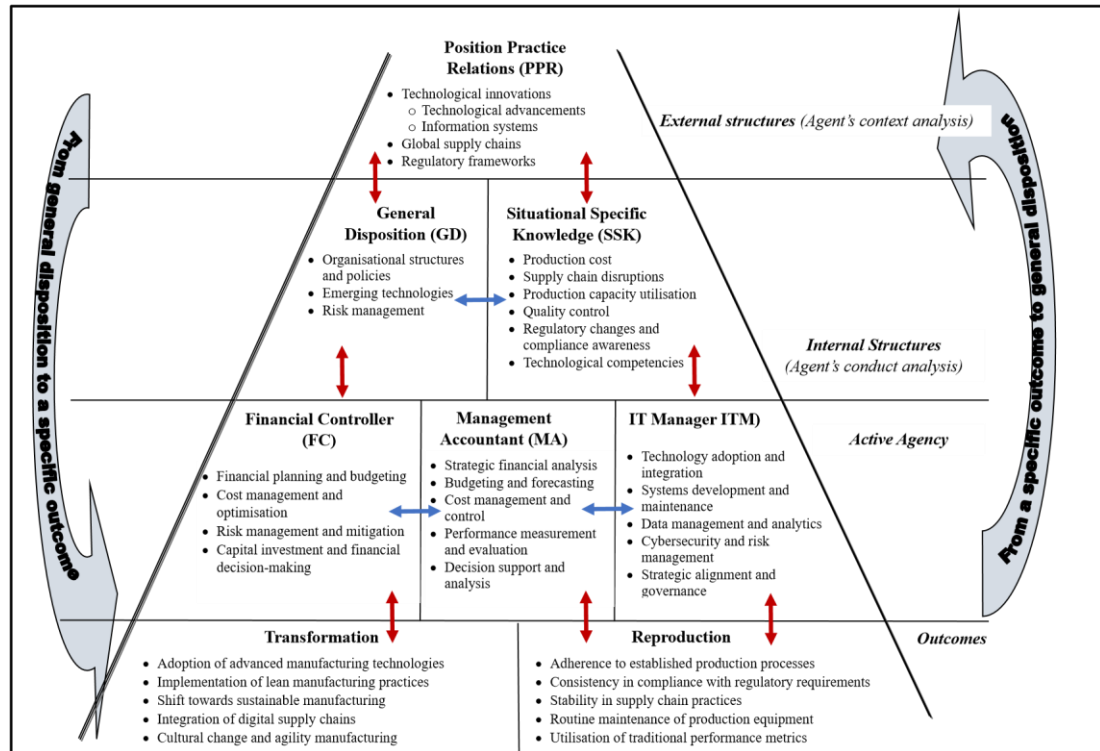


Figure 9: Reverse Funnel approach to data analysis using SST [adapted from Stones (2015)]

Stones (1996) suggests the idea of "strategic context analysis" (which builds on Giddens' concept of "strategic conduct analysis"), placing a greater emphasis on the agent and equating strategic context to "knowledgeability". Knowledgeability applies in strategic conduct because actors use their awareness to enact social practices. Strategic context analysis, in contrast, focuses more on the social links between interdependencies, rights and obligations, and power imbalances. It frequently brings us back to the agent herself, her automatic observation, her intentions, and her aspirations. Stones (1996) acknowledges that the "strategic conduct analysis" is helpful when it is important to understand certain actors' intentions, level of competence, and knowledge. "Strategic context analysis", however, is more helpful in understanding an agent's strategic environment, which limits the possibilities open to them (Conrad, 2014).

4.3.2.1 Bracketing External Structures (Agent's context analysis):

External structures include the regulatory framework (government regulation or industry standards), technological innovations and the global supply chain (due to increased globalisation). Examining the food safety regulations, health and safety standards, environmental laws, and industry standards that govern the company's operations can help unravel how BDA facilitates MCS implementation in the agrifood and beverage industry. Understanding the company's rules, procedures, hierarchy, and resource allocations that shape how work is conducted (organisational policies) can also clarify how MCS design may influence BDA demands.

Agent context analysis refers to how individuals or agents make sense of their social environment and use that understanding to guide their actions. Strong structuration theory posits that human action is not simply a response to external stimuli but a product of the interaction between individuals and the social structures in which they exist (Stones, 2005). Agent's context analysis emphasises the importance of understanding the dynamic relationship between individuals and their social environment (individuals' role in shaping and transforming that environment).

Stones and Jack (2016) suggest that accounting research can be further developed by basing our analysis on understanding the status and adequacy of the knowledge on which people act to produce and reproduce structures. Understanding the use of BDA to facilitate MCS functions within the agri-food and beverage industry requires understanding the external and internal factors that influence this relationship. The usefulness of BDA is primarily determined by factors external to the users, a situation depicted in the quadripartite nature of structuration as external structures. External structures in the agri-food and beverage industry include technological innovations, regulatory frameworks (government regulations or industry standards), and a global supply chain (due to increased globalisation). Agent context analysis enables researchers to understand how individuals or agents perceive and interpret their social environment, and use that understanding to inform their actions. Some examples of external structures prominent within the agri-food and beverage industry are technological innovation, regulatory frameworks and global supply chains (Figure 9).

Technological innovations

External technological developments, such as automation, digitalisation, robotics, and advanced manufacturing processes, create new opportunities and challenges for the agri-food and beverage manufacturing industry, influencing production methods, supply chain management, and competitive advantage. Most participating organisations operate on a tight budget and rely on off-the-shelf software applications rather than bespoke applications to collect data. Software vendors decide which modules to include, along with the possibility of customising to some extent. Ontologically, IT software service providers are treated as external agents when examining the use of BDA to facilitate MCS in the agri-food and beverage industry. Stones (2005:109) describes the external structure as “independent forces and pressuring conditions that limit the freedom of agents to do otherwise”. Therefore, the software can be considered abstract ontological (Stones, 2005). Since its core functionality is predetermined during development, some customisation is allowed for the user.

Stones (2005) recommends distinguishing external structures from the more systemic level conception of conventional social structure. In other words, managers' actions should not be judged by the software package itself, but by its outcomes, as they may not have been involved in defining the software package's specifications. Hence, this study gathered data from an IT service provider to establish their role in using BDA to facilitate MCS.

Regulatory frameworks

Food and beverage manufacturing is a key component of modern economies, with organisations required to ensure food safety through traceability systems (Food Safety Authority of Ireland (FSAI), 2024), which has also been welcomed by consumers (Tran et al., 2024; Vriezen et al., 2023). While this is becoming more prevalent worldwide (Charlebois et al., 2024), it remains challenging for agri-food and beverage manufacturers to design and implement traceability systems. Agri-food and beverage manufacturers have made significant investments in these systems to ensure compliance, but are now viewing them as sources of management information to enhance performance. Given the significant volume of data within these systems,

management accountants are turning to BDA to get insights from the data to inform their MCS.

Global Supply Chain

Globalising markets, production networks, and supply chains connect the agri-food and beverage manufacturing company to a complex web of external structures, including international trade agreements, logistics networks, and geopolitical dynamics (Tseng *et al.*, 2022; Kazancoglu *et al.*, 2024; Slutskiy, 2025). External structures related to outsourcing, offshoring, and global sourcing strategies influence the agri-food and beverage manufacturing company's supply chain design, sourcing decisions, and production outsourcing practices (Cosimato and Vona, 2021; Kazancoglu *et al.*, 2024).

4.3.2.2 Bracketing Internal Structures (Agent's conduct analysis):

The agent's context analysis looks from the actor outwards into the field. In contrast, the other form of methodological bracketing, agents' conduct analysis, looks inward into the actor to establish how the agent deals with that whole process of understanding the context out there concerning their values, duties, obligations, orientations to the world, and so how they come to act in one way rather than another (Coad, Jack and Kholeif, 2016). Agent's conduct analysis guides the examination of how agents (individuals or groups) behave within the structures of society.

Agent context analysis enables researchers to understand how individuals or agents perceive and interpret their social environment, and use that understanding to inform their actions (Stones, 2005). Internal structures include the agent's knowledge, dispositions, and capabilities. Stones (2005) further divides them into general dispositions or habitus and situational knowledge (Figure 9): General dispositions refer to ingrained habits and dispositions shaped by long-term socialisation, while Situational knowledge refers to the role or position occupied by an agent or cluster of agents (Stones, 2005). While general disposition contributes to the continuity and reproduction of social structures, context-specific knowledge enables individuals to engage with and potentially alter social structures through targeted actions and decisions. When analysing general dispositions, the researcher investigates how

ingrained habits, norms, and values shared among employees may influence their use of BDA to facilitate MCS (Huikku *et al.*, 2024). Management's attitudes toward key strategies, such as quality control, determine the effective use of BDA to assist MCS. Also, the extent to which leadership approaches and management philosophies are likely to be internalised by employees at different levels affects their use of BDA to facilitate MCS.

Situational knowledge refers to the situational or context-specific knowledge that a Financial controller in an agri-food and beverage manufacturing company possesses about the immediate financial environment (Feeney and Pierce, 2016). Using information gathered by the management accountant, the financial controller oversees the making of daily decisions. Hence, these two roles provided the primary data from each case study. Where possible, the study also draws on knowledge from other proxy roles, such as IT managers and IT service providers, who contribute to the effective use of BDA in facilitating MCS. Situational knowledge emphasises the proactive role of agents in shaping their social and organisational environments through informed decision-making, strategic action, and the continuous interpretation of the structures they encounter (Harris *et al.*, 2016; Jack, 2017; Huikku, Karjalainen and Seppälä, 2018).

Human actions are situated within specific social environments, shaped by the particular circumstances, norms, and constraints of that context. Several factors (controllable and non-controllable) influence how people use BDA to facilitate MCS. Suppose there are no restrictions imposed by the external structures (IT systems, in this case); SST suggests two different aspects of the relationship between social structures and individual agency. Stones describes these two aspects of an agent's internal structures as generalisable or habitual, leading to the agent's internal structures possibly being divided analytically into two components. Stones (2015) coins the generalisable aspect as “general disposition” and the specific aspect as “situational knowledge”. Both aspects are oriented towards a particular job or task, such as the agent's role in using BDA to facilitate MCS. Still, Stones advocates a separation between the actor's knowledge and the resources available to enable them to attain specific organisational goals. Building on Bourdieu's notion of habitus, Stones' (2005:87) use of ‘general’ in general-dispositional serves as a clearly labelled contrast

with the more contextualised knowledge of particular conditions of action indicated by situational-specific structures. In simple language, general dispositions (or habitus) are the agents' knowledge of themselves and situational knowledge of their role, position and external structures and agents (Jack, 2017).

General disposition refers to individuals' enduring dispositions or capacities arising from their position and past experiences, often acquired through socialisation, and encompassing cultural norms, values, habits, and skills. “This realm is embedded in corporeal schemas and memory traces and is best conceptualised as existing, for the most part, in a taken-for-granted and unnoticed state” (Stones, 2005:88). These relatively stable dispositions shape individuals' actions across various situations and contexts. Sometimes, the agent may not be aware of the dispositional or habitus and may not even notice that they are basing their actions on it. For example, an IT-savvy finance controller would be more likely to make the best of the organisation's ERP system. Jack and Kholeif (2007) alluded to the possibility that some outcomes may be unintended but arise from the resistance generated between the structures and actions envisaged by external agents and between internal agents influenced separately by external agents and the agents-in-focus. The interplay between the external structures and the agent's general disposition is crucial to understanding the efficient use of BDA to facilitate MCS. These general dispositions reflect how the financial controller's actions and decisions are shaped by individual agency and the broader social structures inherent in the agri-food and beverage manufacturing company's financial environment, as originally conceptualised by Giddens (1984).

Situational knowledge, on the other hand, refers to individuals' context-specific knowledge of their immediate environment. Unlike general dispositions, situational knowledge is highly contingent upon the particular circumstances, events, and interactions occurring in a given context. Thus, situational structures provide the critical link between an agent's internal and external structures, as analysing the agent's situational internal structures leads us through the agent into his external terrain (Feeney and Pierce, 2016). This type of knowledge includes information about the current state of affairs, others' intentions and behaviours, available resources, and prevailing norms and expectations. The conditions of an agent's action are related to

its situational internal structures (Feeney and Pierce, 2016). Therefore, situational knowledge is crucial for individuals to navigate and make sense of their immediate social environment and to adapt their actions accordingly. Coad et al. (2016) found that managers in different parts of the same organisation respond differently to accounting information, and their use of this information derives as much from their own dispositions and internal situational structures as from the objective characteristics of the structures with which they interact. For example, managers are more likely to use the organisation's IT efficiently if they are involved in the SDLC, during which the company's strategies are incorporated into the system design. By analysing similar roles in different agri-food and beverage manufacturing organisations, we can identify best practices for using BDA to facilitate MCS.

Contextually specific knowledge refers to people's knowledge and awareness of their immediate social environment, whereas generic disposition refers to the persistent dispositions people bring to different settings. Both are crucial to understanding SST because they influence how people perceive and react to social structures, as well as how those structures are continually reproduced and transformed through people's activities. It can be argued that, however good a software application may be, its successful use depends on the people and other organisational structures in place.

4.3.2.3 Active agency:

SST offers new avenues for collecting and theorising empirical data, as it enables analysis of active agency from an agent's conduct and their understanding of their context. This approach emphasises the quadripartite aspect of agency by analysing the interaction between active agency, external structures, and internal structures to achieve the outcomes. This study elucidates the role of the financial controller, management accountant and the IT manager within a web of position-practice relations (Figure 9), which helps us understand how their actions are shaped by, and how they, in turn, shape, the social structures around them. By analysing the agent's conduct, the research highlights how the financial controller, management accountant, and IT manager interpret their environment and how the resources at their disposal influence their practices. SST allows for a detailed investigation into the enabling and constraining features of the BDA and MCS structures that impact the day-to-day

management of resources, providing a comprehensive framework for empirical analysis in this study (Englund and Gerdin, 2011).

SST provides a lens with which the active agent can be analysed into agent-in-focus and agent-in-situ. The term agent-in-focus refers to analysing the agent as an active agent within the structure, while agent-in-situ refers to analysing the agent as a product of the structure (Jack and Kholeif, 2007). Literature posits the expectation that the Financial Controller is involved in decision-making regarding investment in IT to collect and analyse data (Jack and Kholeif, 2008; Warren and Jack, 2018). Similarly, the management accountant utilises the resources to collect and analyse data from the production floors, cognizant of the financial controller's decisions and the MCS's wider structure. Meanwhile, the IT manager responds to and provides recommendations for IT resources. Our analysis considers these three roles as they have different perspectives and responsibilities on how BDA facilitates MCS.

The external structures constrain and enable the production and reproduction of outcomes (Englund and Gerdin, 2011). According to Stones (2005), external structures provide the agents' conditions of action. He describes them as "independent forces and pressuring conditions that limit the freedom of agents to do otherwise" (p. 109). He distinguishes between independent causal influences and irresistible causal forces. In cases of independent causal influences, external structures are created, replicated, or altered without the agents' consent. In addition, irresistible causal forces, which are forces where an agent can resist an external effect but feels powerless to do so, may also directly impact the agent's actions. Stones (2005: 85) describes active agency as "how the agent either routinely and pre-reflectively, or strategically and critically, draws upon her internal structures".

The strength of SST as a framework for empirical data collection and analysis comes from the analysis of active agency arising from an agent's knowledge of context and conduct (Jack, 2017). She further suggests that active agency helps analyse situations in which people might be able to alter their own or others' internal structures whilst external structures remain seemingly unchanged. Active agency in accounting shifts from the report, artefact, or event to the study of processes, thoughts, messages,

motivations, and intentions, achieved through persuasive communication, decisionmaking, and arguments (Jack, 2017). Building on Coad et al. (2016), this study analyses variations in the ways agents draw upon structures, unreflectively or critically, and how they act to reproduce or change structures, routinely or strategically. Though the perceptions and actions may be at the company-specific ontic level within the industry, these changes in conduct and context are significant in understanding how BDA can facilitate MCS. Agency refers to individuals' capacity to act independently, make their own choices, and impose those choices on the world. Agents are those who possess this capacity, fully or partially. Agents, therefore, are not merely passive products of social structures but active participants who both shape and are shaped by them.

Stones (2005: 114-115) identifies three properties the agent would need to be able to resist: (1) adequate power, (2) adequate knowledge of alternative possible courses of action and their consequences, and (3) adequate critical distance to take up a strategic stance about a particular external structure and its situational pressures. Agent-infocus refers to agents who possess all three properties; otherwise, they are agent-insitu. By employing multiple perspectives within the organisation, the study aims to isolate the “independent causal influences” that affect the agent-in-focus, as well as the “irresistible causal forces” the agent-in-focus may be able to work with and resist, acknowledging that different agents may perceive the same phenomenon in different ways. Agent-in-situ refers to an agent situated within a particular social and spatial context (specific environment or situation in which an agent operates) and may not possess adequate power to resist.

Stones (2005) states, “external structures as conditions of action, which have an existence that is autonomous from the agent-in-focus, and which within structuration are conceived in terms of the structural context of actions faced by that agent-in-focus at time 1”. Irrespective of the agent-in-focus’s knowledge, their actions and the consequent outcomes depend on the quality of the software package at their disposal. For example, the software package, as a resource, may limit individuals' actions, but it can also provide resources and opportunities. Sometimes, the agent-in-focus may be involved in the design and development of the software package (System Development

Life Cycle - SDLC). The level of involvement for organisations operating in a tightbudget industry, such as the agri-food and beverage industry, may not be adequate. Suppose the organisations were more involved in the design of the software package; the resulting software package would incorporate the software vendor's know-how and the organisation's specific strategic requirements. Generally, data derived from bespoke applications is likely more helpful than that from on-the-shelf applications.

These structures may exert independent causal influences when they are autonomous from the agent-in-focus. Independent structures mediate (constrain and enable) action, but their reproduction is irrelevant to the agent-in-focus (Makrygiannikis and Jack, 2016). The regulatory framework for the agri-food and beverage industry remains the biggest independent structure mediating these companies' financial transactions. Food safety and traceability are not requirements that any agri-food and beverage company can choose to ignore. Hence, they collect data to comply with the regulatory requirements and to please their customers. The financial controller (agent-in-focus) is responsible for this and has the power to ensure its fulfilment. In contrast, the management account or the IT manager, who relies on instructions from the financial control, does not fully possess this capacity and therefore occupies the status of an agent-in-situ. Based on the agent's capacity , the outcome could have far-reaching effects (transformational) or limited effects (reproductional) on the organisation.

4.3.2.4 Outcomes

Outcomes complete the loop of the quadripartite circle of structuration by feeding back into the position-practice network. Outcomes define how external and internal structures are reproduced or changed (Stones, 2005). Consistent with the ontology of structuration, outcomes may be intended or unintended, agents may be successful or unsuccessful in their endeavours, and structures may be sustained or altered (Kennedy, O'Gorman and Lee, 2021). Drawing from SST, transformational outcomes in agrifood and beverage manufacturing companies involve significant changes in organisational structures, practices, and interactions resulting from the interplay between individual agency and social structures. Meanwhile, outcomes considered reproductional involve perpetuating or reproducing existing organisational structures, practices, and norms (Stones, 2005). Reproductional outcomes reflect the ongoing influence of social

structures on individual actions and the reinforcement of established patterns within the organisation. Employing BDA techniques in managing the company's MCS would generate transformational and reproductional outcomes. Adopting advanced manufacturing technologies and shifting towards sustainable manufacturing represent transformational outcomes. Similarly, consistent compliance with regulatory requirements and adherence to established production processes are good reproductional outcomes.

4.4 Chapter Summary

SST offers a holistic perspective that considers agency and structure, providing a comprehensive understanding of the social dynamics within the agri-food and beverage manufacturing industry. The theory allows the researcher to analyse interview data within the agri-food and beverage manufacturing industry, considering the unique organisational structures, work practices, and technological systems that shape behaviour. SST encompasses several abstract concepts, making its application and operationalisation in practice challenging. Given the complexity and subjectivity of human actions and social structures, applying SST ensures consistency in interpretation.

Chapter 5 Methodology

5.1 Introduction

The previous chapters articulated the motivation for this study. They presented a detailed literature review on the relationship between MCS and data analytics, culminating in a conceptual framework derived from synthesising the literature. This chapter outlines the research design clearly and clarifies the researcher's position adopted within this study. It is common practice for researchers to plan their research around the question that needs answers or the problem that needs to be solved. Having established the question or problem, the researcher then considers the data to be collected and the techniques they may use to collect it. This choice suggests that research is a sequential journey, where the completion of one stage leads to the next. However, Orlikowski (1991) argues that while the methodology is prescriptive in documentation, its tenets are often modified, overridden, or ignored in practice. This argument is echoed by Saunders et al. (2018), who suggest that research is an iterative process, with data collection and analysis at its core. The researcher must explain why they chose data collection techniques and analysis procedures.

The remainder of this chapter presents the methodological voyage undertaken in this study. The journey begins with articulating the research question and objectives that guide the adopted research approach. It then presents arguments to support the underlying assumptions about what constitutes 'valid' knowledge before elaborating on the various research philosophies. The next step outlines the approach to theory development, which informs methodological choices guiding the research strategies and culminates in data collection and analysis techniques and procedures. The chapter concludes by presenting the ethical considerations that guided this study.

5.2 The Research Question and Objectives

Collis and Hussey (2003) define the purpose of research as the reason it is being conducted, whether exploratory, descriptive, analytical, or predictive. Based upon the literature review on MCS and BDA, little is known about how advances in ICT affect the core role of management accounting (Mahony and Doran, 2008; Bettiol *et al.*, 2022; Hung *et al.*, 2024). Furthermore, ICT is intricately linked to decision-making and control in a complex way, challenging the majority of linear explanations produced

by contemporary research (Granlund et al., 2013). For example, Quattrone (2016) argues that the rise of big data has expanded access to digital data within enterprises, potentially affecting decision-making. This rapid data flow may cause managers to make wrong decisions much more quickly than before. Therefore, there is a need to establish how ICT enables MCS and how MCS use ICT. The primary objective of this study is to establish substantial evidence for the use of BDA to facilitate MCS in the agri-food and beverage industry, specifically identifying what works and what does not in various settings. As a result, the research question that drives this research is as follows:

How do agri-food organisational actors interpret external pressures when using Big Data-enabled control systems, and how does this shape whether control practices are reinforced or changed: A strong structuration theory approach?

Research objectives:

1. *How do industry-level analytical developments constitute external structural conditions that shape the use of management control practices in the agri-food and beverage industry?*
2. *How do organisational actors draw upon Big Data Analytics within their internal structures when implementing management control practices?*
3. *How do organisations' position-practice relations enable or constrain the use of BDA-enabled MCS?*
4. *How does the agency of management accountants contribute to the reproduction or transformation of control logics and data-driven decisionmaking practices over time?*

It is common knowledge that the agri-food and beverage manufacturing industry (like all modern businesses) uses some form of BDA. However, the extent of usage of these tools will inevitably differ from one company to another. Consequently, the research paradigm adopted aims to determine how BDA helps to manage the organisation's resources. This study collects empirical data to determine whether agri-food and beverage manufacturers are effectively utilising their BDA capabilities, identify existing barriers, and recommend strategies to mitigate them.

5.3 Research Methodological Approach

A research methodological approach refers to the systematic plan employed in research, encompassing the overarching framework, data collection methodologies, and analytical tools. It dictates the design, execution, and interpretation of a study (Saunders, Lewis and Thornhill, 2007; Bryman, 2015; Denzin and Lincoln, 2017; Creswell, 2018). This procedure entails articulating the researcher's philosophy, delineating the research design, and elucidating the data gathering methods and analytical tools employed in the study. The research must elucidate the validity and reliability of the proposed methodology for the results to be authoritative. The following sections provide a comprehensive overview of the research methodology employed in this study.

5.3.1 Research Philosophy and Paradigms

Creswell (2018) states that research philosophy is the researcher's belief in how data concerning a phenomenon should be collected, analysed and applied. All research is based on certain assumptions about what is considered 'reasonable' knowledge. These assumptions guide the researcher's quest for knowledge. Saunders et al. (2018) recommend choosing a research philosophy based on its suitability to the research question and not on which one is better. Accordingly, the philosophical positioning of a piece of work is the first step in the research design. Saunders et al. (2018) suggest that philosophical positioning is rooted in a paradigm, a set of basic beliefs (or metaphysics) that deal with ultimate or first principles (Guba and Lincoln, 1994).

A research paradigm is a set of fundamental assumptions and beliefs regarding how the world is perceived, which then serves as a thinking framework that guides the researcher's behaviour (Jonker and Pennink, 2010). While research philosophy refers to the philosophical assumptions a researcher holds about the research (Ylijoki and Oy, 2019), research paradigms address the philosophical dimensions of the social sciences (Wahyuni, 2012). Kuhn's (2012) introduction of research paradigms has guided researchers to address the philosophical dimensions of social science research. He first coined the term paradigm in 1962 to describe philosophical thinking (the set of practices, norms, and accepted theories that define scientific research in a particular period). Paradigms are considered amalgams of scientific practices and conceptual

schemes (Preston, 2008). The two dominant research paradigms have resulted in two research cultures, one professing the superiority of ‘deep, rich observational data’ and the other the virtues of ‘hard, generalisable data’ (Johnson and Onwuegbuzie, 2004). O’Gorman and MacIntosh (2015) consider it good practice to clearly outline the basis for claiming to know what we know when undertaking any research project. In other words, philosophical assumptions that influence the nature of the knowledge produced in research must be identified (Creswell, 2018) and maintained throughout the research journey (Kuhn, 2012).

Lincoln and Guba (1985) suggest that a paradigm consists of four components: ontology, epistemology, methodology and axiology. This study adopts Guba and Lincoln’s (1994: 105) definition of paradigm as follows:

“The basic belief system or worldview that guides the investigator not only in choices of methods but in ontologically and epistemologically fundamental ways”

Ontology

Ontology concerns how researchers perceive reality, which, in turn, influences their understanding of how the world operates. The researcher’s perception of the world influences what they want to understand and thus shapes their research approach. Two core aspects of ontology explain the researcher’s position on reality: objectivism and subjectivism. Objectivism is based on the assumption that social phenomena and their meanings exist independently of social actors (Bahari, 2010). In contrast, subjectivism is an ontological position based on the assumption that social phenomena are created from the perceptions and actions of social actors (Saunders, Lewis and Thornhill, 2023). This study assumes the idea or view that social life is the product of social interactions and the beliefs of the social actors (Bahari, 2010). A study of the application of information technology cannot be a linear cause-and-effect relationship, as many factors, such as people, strategies, and software/hardware, would determine its success.

Epistemology

Epistemology is concerned with what constitutes adequate knowledge in a field of study – essentially, how do we know what we know? (Saunders et al., 2012; Budd, 2004). The central issue in epistemology in the social sciences is whether the social world can and should be studied according to the same principles and procedures as in the natural sciences (Bahari 2010). The term epistemology is commonly described as being concerned with the creation and dissemination of knowledge in particular areas of inquiry (Steup, 2014). Steup's (2014) definition of epistemology states that epistemology studies knowledge and justified belief. Research philosophy allows the researcher to reflect on how each philosophy's ontological and epistemological stance shapes their view of what constitutes adequate knowledge and guides methodological choice accordingly. The main branches of research philosophies include positivism, interpretivism, critical realism, pragmatism, and constructivism/postmodernism.

While building on the works of Lincoln and Guba, Appleton and King (2002) distinguish between constructivism and postmodernism in many ways. Despite their similarities and differences, neither philosophy applies to this study, as the researcher must be deeply involved with the participants. Pragmatism, on the other hand, holds that reality has multiple views and that knowledge is both objective and subjective. This study aims to investigate how BDA facilitates MCS and seeks to develop a corresponding framework. Positivism is unsuitable because it posits reality as objective, stable, and real. This study believes multiple factors would influence the successful use of BDA technologies to facilitate MCS. The knowledge of how BDA facilitates MCS is subjective and context-dependent, based on human experiences, interpretations, and meanings. To adequately understand the relationship between these two phenomena, the researcher must have a deep understanding of participants' perspectives, cultural contexts, and lived experiences. The researcher, therefore, engages closely with participants but does not participate in the research themselves, as explained in Section 5.4.6 (Researcher's Positionality). Thus, interpretivist philosophy best suits this study, as it seeks to explain the causal mechanisms behind the use of technology to facilitate an organisational strategy that humans execute.

The practical implementation of a technology or strategy relies on various elements, including the technology's attributes, the strategy's resilience, and the individual's

ability to execute it appropriately. Other factors can also influence each mitigating factor. For example, the MCS may be influenced by the organisational structure within a given organisation or the individual's exposure to the technology being implemented. The nuances influencing the use of BDA to facilitate MCS can primarily be established through an interpretivism paradigm. This critical approach is enabled by SST, which provides a comprehensive framework for analysing qualitative data to comprehend the intricate interplay between external and internalised structures within the agri-food and beverage industry.

5.3.2 Approach to Theory Development

Collis and Hussey (2003) define the research logic as whether the research moves from general to specific or vice versa. Research methodology refers to a systematic approach to inquiry that encompasses the foundational philosophy of a study, the design of the research process, and the subsequent stages of data collection and analysis (Saunders, Lewis and Thornhill, 2007; Goundar, 2012; Patel and Patel, 2019; Kothari, 2024). Theory development in qualitative research is generally an inductive and interpretive process where theories emerge from data rather than being imposed before the study begins (Bingham, 2023). Several authors have offered interpretive and inductive approaches to research synthesis, which are more likely to draw insight from studies and address issues pertinent to management research (Tranfield, Denyer and Smart, 2003). Hatch (2002) asserts that researchers spend extended periods interviewing and observing participants in their natural settings to reconstruct the constructions participants use to make sense of their worlds. He further suggests that hermeneutic principles guide researchers' critical constructions of participant perspective. Hatch's (2002) assertion and suggestion align with this study's aspirations, as the researcher seeks to explore how agri-food and beverage manufacturing companies use BDA to facilitate MCS.

In addition, the unstructured and yet less complex phenomena being examined in this research imply that a fundamental structured or unstructured approach is inappropriate. A semi-structured approach was adopted to avoid creating a methodical "tunnel vision" that would limit interpretation of the collected data, while allowing the research to focus on the studied phenomena. Maxwell (2013) points out that structured

approaches can help ensure the comparability of data across individuals, times, settings, and researchers and are thus valuable for answering variance questions that examine differences between things. Meanwhile, unstructured approaches allow the researcher to focus on the particular phenomena being studied, which may differ from others and require individually tailored methods (Maxwell, 2013).

Much research involving information technology and financial management within the agri-food and beverage manufacturing industry has largely adopted a qualitative approach (Bruque and Moyano, 2007; Bedford, Malmi and Sandelin, 2016; Kapasi and Galloway, 2016; Trigo, Belfo and Estébanez, 2016). Literature identifies the three research approaches as inductive, deductive and abductive (Dubois and Gadde, 2002; Kovács and Spens, 2005; Chamberlain, 2006; Thomas, 2006; Graebner, Martin and Roundy, 2012; Timmermans and Tavory, 2012; Gioia, Corley and Hamilton, 2013; Eisenhardt, Graebner and Sonenshein, 2016; Costa, Lucas Soares and Pinho de Sousa, 2017; Kennedy and Thornberg, 2018). These approaches vary in logic, reasoning processes, and how they generate knowledge or draw conclusions (Spens and Kovács, 2006).

Eisenhardt et al. (2016) use the term “inductive” to underscore the core emphasis on the emergence of theory from data rather than simply on a type of data. Inductive methods are those approaches that researchers attempt to generate theories or explanations from data (Gioia et al., 2013; Eisenhardt et al., 2016). Inductive methods seek to develop a new theory from data (in research practice) or empirically expand on an existing theory that has not been fully exploited. In induction, researchers use a series of empirical cases to identify a pattern from which to make a general statement; thus, inductive logic consists of inferring categories or conclusions based on data (Kennedy and Thornberg, 2018). They further suggest that induction closely aligns with the data and can reveal new insights into existing knowledge and conclusions. Meanwhile, abduction refers to creative inference and double-checking these inferences with more data, which fits in with the formal grounded theory recommendation to move back and forth between data and theory iteratively (Timmermans and Tavory, 2012). Sitting between inductive and abductive methods is

the deductive approach, which is concerned with developing propositions from current theory and making them testable in the real world (Dubois and Gadde, 2002).

Adopting an abductive approach was most appropriate for understanding the complex relationship between BDA and MCS, thereby developing a best-practice framework for their use within a typical management accounting function. This approach is most suitable for this study since it seeks to answer the questions of why, when, and how management uses BDA to manage the company's finances on a day-to-day basis. While the richness of qualitative data is useful for inspiring and deepening theory, flexibility is the most fundamental advantage for theory-building (Graebner, Martin and Roundy, 2012). Gioia et al. (2013) see the qualitative research approach as a flexible orientation, open to innovation rather than a "cookbook," as critics may suggest. This study explores hard-to-measure constructs because multiple factors influence the use of BDA in implementing MCS. It will be challenging for a single measure to account for all aspects or components of the situation under investigation, because different methods of measuring BDA from different perspectives may yield different results. Therefore, the emphasis is on understanding and acknowledging the context in which BDA is applied to facilitate MCS, as well as the challenges that impede its successful implementation. The abductive approach requires researchers to collect and analyse data, identify patterns, and derive general principles or theories from these patterns (Mezmir, 2020; Gamage, 2025). Abduction involves making creative inferences and subsequently verifying these inferences with supplementary data. This practice corresponds with the formal grounded theory approach, which advocates for an iterative movement between data and theory (Timmermans and Tavory, 2012). The study employs various theories to understand the implementation of technology and organisational change. Each of these theories has its merits and demerits, depending on the study context, and is identified and analysed later in this chapter.

5.3.3 Methodological Choice

Researchers must provide a rationale for selecting a methodological approach that best aligns with their research question. As explained later in this chapter, this decision affects the study's reliability, validity, and overall contribution. Collis and Hussey

(2003) define the research process as collecting and analysing data, and it requires a clear articulation of the methodological choice adopted in the study.

Due to the diversity of methodological choices, each researcher must explore and define research within their integral framework (Roulston, 2008). This stage in the research process involves carefully considering the research strategy and specific methods that best address the research question and objectives. Based on Saunders et al.'s (2018) onion metaphor, methodological choices represent the third stage in the research process. It is a crucial stage in the research process that seeks to minimise methodological determinism, as highlighted by Sedmak and Longhurst (2010), who suggest that awareness of methodological options reduces the risk of “methodological determinism”. Methodological determinism holds that the researchers' methodologies dictate and constrain how they approach the subject and formulate study questions. Researchers should understand various epistemologies, paradigms, or traditions to grasp the range of available approaches; hence, many authors caution against ‘epistemological determinism’ (Mogensen, Caswell and Trick, 2007). Thus, the research objectives, data collection and analysis procedures, and findings presentation should all be connected by a methodological approach that aligns with the study's philosophical presumptions (Eisenhardt and Graebner, 2007; Creswell, 2018; Yin, 2018).

This study aims to deepen the understanding of how BDA facilitates MCS in the agrifood and beverage manufacturing industries. Such a deep understanding can be best achieved through a qualitative research approach, which provides detailed insights from multiple perspectives. As Roberts (2014) puts it, qualitative methods are arguably more attuned to the “messiness” and “openness” of real social life (e.g., the overlapping social identities we all inhabit daily), which inevitably affect the outlook of respondents in their everyday lives. For a study aiming to navigate such intricacies to uncover the nuances of using BDA to facilitate MCS, it is logical that the researcher adopts an abductive approach with subjective insight to fully capture the experiences, beliefs and perspectives of key actors involved (Ritchie and Lewis, 2003; Schmidt and Schmidt, 2009). One of the most common approaches to qualitative research is the use of case studies, given the richness of the data collected. The richness derived from the

case study approach comes from the multiple perspectives. The multiple perspectives may come from various data collection methods, which may also derive from multiple accounts - collected using a single method from people with different perspectives on what is being studied (Eisenhardt, 1989; Ritchie and Lewis, 2003; Bluhm *et al.*, 2011; Briggs, Clark and Hall, 2012). Using multiple data sources and involving multiple participants ensures data triangulation, allowing significant insights to emerge (as elaborated in subsequent sections).

5.3.4 Research Strategy

While research methodology is the conceptual and philosophical basis that justifies this plan, research strategy is the practical plan for conducting the research. The research strategy sits in the fourth layer of the research onion and is crucial for defining how the researcher collects and analyses data to answer the research question. The research strategy adopted is a direct consequence of the methodological choice made in the previous layer of the onion metaphor. Up to this point, amid the methodological meandering, it has been articulated that this research study aligns with an interpretivist philosophy, approaching theory development through abduction, and that findings are generated through qualitative data collection and analysis methods. Given the range of philosophical perspectives described earlier, several qualitative research methodologies are available for collecting and analysing data to answer research questions. John Creswell formally identifies and categorises the five main approaches to qualitative research in his foundational texts, such as *"Qualitative Inquiry and Research Design: Choosing Among Five Approaches"*. He identifies the five approaches as narrative, ethnography, phenomenology, grounded theory, and case study. A multi-case study approach was determined to be most suitable for this study, as explained below.

Multiple case study research

The researcher adopted an exploratory qualitative approach, using semi-structured interviews with industry experts, to investigate how BDA facilitates MCS. This choice of methodology is justified, as it provides in-depth insights into the nuances of using BDA to facilitate MCS. The exploratory nature of the study requires a methodology that promotes flexibility and adaptability, allowing the researcher to investigate the nuances and complexities of the research topic, ask follow-up questions, and explore

emerging themes (Pozzebon, 2000; Ritchie and Lewis, 2003; Gill *et al.*, 2008; Creswell and Poth, 2018).

Yin (2014: 16) sums up the scope of a case study in a single definition as follows: “*A case study is an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not evident*”. This study aims to investigate how BDA is utilised to facilitate MCS. The findings of this study are based solely on statements from participants and a review of documents from the participating case study, which are grounded in a theoretical foundation. The interview questions were designed to ensure that all information came from the participants without undue influence from the researcher, as explained in section 5.4.6 (researcher’s positionality). The selection of food and beverage companies was based on their process-intensive manufacturing systems, which generate large volumes of data that may necessitate BDA. The selection of cases was necessarily constrained by issues of access and organisational willingness to participate, a pragmatic reality in qualitative field research that prioritises depth over breadth, yet one that nonetheless introduces the possibility that the findings reflect the particular characteristics of those organisations that opted into the study. The researcher posits that various factors impact the utilisation of BDA to enhance MCS within the agri-food and beverage industry. The use of BDA to facilitate MCS may be influenced by external or internal factors, as well as by the potential of the personnel responsible for its implementation. A multiple-case study approach is adopted since there are no clear boundaries between the phenomenon and the context under investigation.

A multiple case study design is a robust qualitative research methodology that entails the examination of multiple cases to investigate a phenomenon, evaluate a theory, or develop new theoretical insights (Kowalczyk and Buxmann, 2015; Yin, 2018; Ardolino *et al.*, 2025). A multiple case study approach involves examining two or more cases simultaneously or sequentially to gain a deeper understanding of a particular subject (Safari, McKenna and Davis, 2023). Yin (2018) claims that multiple case studies are advantageous as they meet the conceptual criteria for theoretical or literal replication and support analytic generalisations. Halkias *et al.* (2022) recommend the

multiple case study design as an effective qualitative research method for examining the relationships among personal, social, behavioural, psychological, organisational, cultural, and environmental elements that influence organisational and leadership development. This study aims to investigate how individuals within the agri-food and beverage industry utilise BDA to facilitate MCS. The study also aims to identify the nuances around the two phenomena. For example, how does the use of BDA help in the implementation of MCS, and how does MCS design influence organisations' demand for BDA technologies? This relationship, involving personal, social, and organisational elements, is best studied using a multiple case study design that collects data primarily through interviews and other supporting methods.

5.4 Data Collection: Techniques and Procedures

Many data collection methods can be used, including direct observation, participant observation, interviews, focus groups, documentary sources, archival records and physical artefacts (Creswell, 2018; Saunders, Lewis and Thornhill, 2023). As stated earlier, this study adopts a qualitative case-study approach, allowing the researcher to explore complex relationships among individuals, systems, and organisations that use data-analytic technologies to manage their finances. One of the strengths of the case study approach is its flexibility and adaptability, which enable the use of single or multiple methods of data collection in answering the research question (Yin, 2018). Using more than one source of data and involving multiple participants ensures data triangulation and allows significant insights to emerge (Turner and Turner, 2009). Although methodological triangulation can provide completeness, abductive inspiration, and confirmation, Saunders et al. (2018) argue that collecting data through case studies is a multi-method qualitative approach. This study employs multiple case studies, including document reviews, to achieve data triangulation. To further strengthen triangulation, a review of documents on participants' strategies is conducted in tandem with semi-structured interviews with participants at different levels of decision-making responsibility.

Creswell (2007) visualises data collection as a series of interrelated activities to gather good information to answer emerging research questions. Data may be collected in various ways and from various sources, with each collection method presenting its own set of strengths and limitations. While traditional quantitative methods generate

data through instruments such as questionnaires, checklists, scales, tests, and other measuring devices, the principal data for qualitative researchers are gathered directly by the researchers themselves (Hatch, 2002). Two key conceptual issues in selecting and using different data collection methods are the relationship between the research question and data collection methods, and the triangulation of different methods (Maxwell, 2013). While the first concept is almost obvious, triangulation is traditionally conducted at the end of a study, when its validity is assessed. Still, Arksey and Knight (2011) pointed out how triangulation can be used and is fruitful in ongoing research, particularly in collecting qualitative data. The core approach used in this research is a series of case studies, which are discussed next.

5.4.1 Case Study Approach

Yin (2014) defines a case study from two perspectives:

1. Based on the scope, a case study is an inquiry that investigates a contemporary phenomenon in depth and within its real-life context, especially when the boundaries between phenomenon and context are unclear.
2. The second aspect is that other technical characteristics, including data collection and analysis strategies, must be considered because phenomena and context are not always distinguishable in real-life situations.

The first aspect is more relevant to this study, as it seeks an in-depth understanding of the real-world implementation of BDA-enabled MCS. Still, such understanding encompasses important contextual conditions highly pertinent to this phenomenon (Yin, 2018). The contextual conditions include cost-sensitive organisations operating under tight margins that employ BDA to extract valuable data.

A case study is a research approach used to generate an in-depth, multi-faceted understanding of a complex issue in its real-life context (Crowe *et al.*, 2011). This study seeks to understand the world from the perspectives of those living in it; thus, it tries to capture the perspectives that actors (participants) use as a basis for their actions in specific social settings (Hatch, 2002). It is also important to acknowledge the role of the researchers within the world they study. The researcher influences and is influenced by this world, resulting in a mutual relationship that is both a necessary aspect and a facilitator of data collection and a potential validity threat to the research

conclusions (Maxwell, 2018). The SST model developed by Stones (2005) is considered a fit for case study research in accounting, organisation and management (Jack and Kholeif, 2007; Coad et al., 2016). This model provides the researcher with a tool to take a broad view of the application of BDA-enabled MCS and the individuals involved in its implementation within a given organisational setting.

5.4.2 Strategies for Selecting Cases

In selecting cases for this study, Yin (2013) recommends consciously avoiding any form of sampling. Instead, the emphasis is on the criteria for selecting participating case studies. Among the weaknesses of case study research identified by Yin (2014) are the lack of rigour and the fact that it may provide little basis for generalisation. To overcome this challenge, Yin (2014) recommends using multiple case studies, arguing that evidence from multiple cases is often considered more compelling and that the overall study is more robust. Yin (2014) recommends that each case be carefully selected so that it either (a) predicts similar results (a literal replication) or (b) predicts contrasting results but for anticipatable reasons (a theoretical replication).

Given the focus of the study, a key criterion for selecting the case study companies was that they had to be cost-sensitive manufacturing companies that employ or plan to adopt big data principles in their day-to-day operations. While drawing on various contacts to secure access to the case study companies, a shortlist of potential companies was reviewed for suitability. One consideration is to focus on a particular industry, as in Feeney and Pierce (2016), who used this approach to study management accounting practices. This focused approach has a significant advantage: the researcher is immersed in the industry and can thus understand the nuances of practices in more detail.

As explained in Chapter Two, the targeted industry for this research is the agri-food and beverage industry. There are many large agri-food and beverage companies in Ireland, some of which already have established links with the School of Business at Maynooth University. Yin (2013) suggests that for a study to genuinely take advantage of the case study method, that is, by probing a case and its context in-depth, it will likely be able to include only a small number of cases. He further emphasises that the

only way to increase the number of cases to a substantial level would be to sacrifice the in-depth, contextual insights inherent in the case study method. Therefore, eleven case companies and one expert informant were selected to ensure enough depth while allowing for the potential generalisation of the results.

The case studies were carefully chosen. Since finding SMEs with a structured MCS and utilising BDA technologies is challenging, we analysed many agri-food companies in Ireland to identify those that best meet our needs. In each of the participating companies presented below, various roles were interviewed. Interviewees were selected for their expertise in the processes that generate data and for their alignment with the research topics. In the agri-food and beverage industry, the financial controller, management accountant and the IT manager can be regarded as agents-in-focus when analysed through the lens of SST.

The first three companies (identified as C1 to C3) had all three roles (financial controller, management accountant, and IT manager) executed by three separate individuals. Having the three roles allows the analysis to determine how individuals' personalities may influence the company's adoption of BDA. These companies have adopted data analytics techniques to gather information for monitoring and reporting on all their productions. They also employ these techniques to carry out accurate accounting and control activities. These three companies were considered strong sites for this research as the three major roles were managed by separate individuals, allowing the research to corroborate data from each. In addition, the CFOs of eight other agri-food businesses were interviewed to broaden the scope of data capture on strategic implementations with SMEs. These CFOs effectively manage the functions of all three roles. Finally, an IT service provider specialises in providing software systems to agribusinesses and agri-food and beverage manufacturing companies. The IT service provider concurred with the information on the System Development Life Cycle (SDLC), identified in the analytical framework as an influencing factor on the external structures of SST. A total of eighteen interviews were conducted and recorded using Microsoft Teams. The recordings were then transcribed and analysed using NVivo software, as explained later in this chapter. Vitale et al. (2020) describe this approach to case study selection as convenience sampling, as the use of BDA

technologies and a structured MCS was necessary to undertake and answer the research questions.

5.4.3 Case Study Profiles

This section presents an overview of the context of each case study, the sources of evidence that were collected, and the list of participants (anonymised) from each case study. The credibility of case study research is tied to the level of depth and contextualisation achievable when only one or a small number of focus instances are examined; consequently, it is critical to convey expert opinion and viewpoint on the case effectively (Fossey *et al.*, 2002; Morse, 2008; Yin, 2013; Baškarada, 2014; Malterud, Siersma and Guassora, 2016; Braun and Clarke, 2022b). Malterud *et al.* (2016) propose the concept of “information power” to guide the determination of adequate sample sizes for qualitative studies. Information power indicates that the more relevant information the sample holds for the study, the fewer participants are needed. They suggest that the size of a sample with sufficient information power depends on (a) the aim of the study, (b) sample specificity, (c) the use of established theory, (d) the quality of dialogue, and (e) analysis strategy. This study employs information power to ensure that appropriate levels of detail and contextualisation are achieved. Since this study aims to establish how BDA is used to assist MCS, the interviews will focus on the people directly involved in using this technology or a similar one within the case study organisation. By adopting this approach, the researcher ensured high-quality information.

The case profiles present an overview of each case study's context and provide a contextualisation for the reader. The researcher includes case profiles as a mechanism for triangulation in the data analysis, with documentation and interviews providing the data for them. Including multiple sources of evidence can enhance the quality of the research and findings (Yin, 2018). The selection of the case studies considered the variety of products in the agri-food and beverage industry to ensure that participating case studies cover the breadth of the industry. Such diversification aims to gather data from which the results can be generalised within the industry. It can generally be assumed that the external structures are similar in all the case studies. However, the internal structures will likely differ because each company has their own strategies.

The product line of the case studies ranged from meat processing, chocolate, potato crisps, dairy, bakery and animal feed. One of the participants was an IT software company, which allowed the researcher to gain some understanding of the process of matching organisational strategies to the software package. This single company is considered an expert participant because it is not operating in the agri-food and beverage industry. As explained above (5.4.2), the target roles for the interviews are the financial controllers, management accountants and IT managers.

The Financial Controller or Chief Financial Officer (FC)

The financial controller or CFO in the agri-food and beverage exemplifies an agent-in-focus, as they actively mediate between structure (regulations, customer demand and resource management) and organisational agency. The financial controller ensures that the agri-food and beverage company maintains robust financial health, complies with regulatory requirements, and supports its strategic goals, contributing to its overall success and sustainability (Quattrone, 2016; Daff and Jack, 2018). Some of the functions carried out by the financial controller to achieve these goals include interpreting and enforcing financial regulations, implementing investment strategies, managing compliance and risk, and overseeing the overall financial strategy (Drury, 2018; Mesioye and Bakare, 2024). Most importantly, they must ensure operational efficiency through process improvement (streamlining financial processes and systems to reduce costs) and technology integration (using financial software to improve reporting accuracy and speed). These functions and strategies generate and consume a substantial amount of data, necessitating thorough analysis to support informed decision-making.

The Management Accountant (MA)

The management accountant at an agri-food and beverage company plays a crucial role in providing financial insights and support for decision-making to improve operational efficiency and profitability. The management accountant ensures that the agri-food and beverage company operates efficiently, controls costs effectively, and makes informed strategic decisions, ultimately contributing to its financial health and competitiveness (Bakhodirovich, 2023). The functions the management accountant performs to achieve these goals include cost accounting, budgeting and forecasting,

financial reporting and analysis, cost control and efficiency, financial planning and strategy, internal controls and compliance, and support for operational decisions (Ojra, Opute and Alsolmi, 2021; Andrade *et al.*, 2024). The role that most impacts this study is financial systems and technology. The management accountant uses ERP systems to manage and analyse financial data effectively. They implement and use advanced data analysis tools and software to enhance financial reporting and decision-making capabilities, which is one of the principal foci of this study (Mesioye and Bakare, 2024).

Although not all participating companies had a dedicated management accountant role, some did, and the researcher ensured that those with one were interviewed separately from the financial controller to better understand how this role contributes to the adoption and use of BDA. In some cases (smaller companies), only one person was interviewed because that individual was responsible for the functions of the financial controller, management accountant, and IT manager.

The IT Manager

The IT Manager in an agri-food and beverage company plays a critical role in overseeing and managing the company's technology infrastructure, ensuring that IT systems support business operations effectively and securely. They ensure that the agri-food and beverage company's IT infrastructure is reliable, secure, and aligned with business goals, thus supporting operational efficiency and growth. The IT Manager accomplishes these operations through various functions, with data management and analytics being the most relevant to this study. This function requires the IT Manager to implement robust data security measures to protect sensitive company and customer information, utilise data analytics tools to generate insights from operational data, support decision-making processes and manage databases to ensure data integrity, availability, and performance (El-Haddadeh, 2020).

As mentioned above, IT functions may be the responsibility of the financial controller when there is no dedicated IT Manager. Wherever participating companies had a dedicated IT Manager role, the researcher ensured that the IT Manager was

interviewed separately from the financial controller to better understand how this role contributes to the adoption and use of BDA.

IT Service Provider

IT service providers are critical to the successful implementation, maintenance, and optimisation of IT systems for an agri-food and beverage company. They ensure that the agri-food and beverage company leverages its IT system to enhance efficiency, maintain compliance, improve decision-making, and ultimately achieve its business objectives. From the researcher's experience in the software industry, software developers rely on their clients to provide crucial information during the system analysis phase. Involving clients in the SDLC ensures that the software aligns with the client's organisational strategies. However, software developers cannot ensure the involvement of all clients in the SDLC and will therefore develop some OTC applications (with the possibility of customisation). Interviewing an IT service provider sheds light on their approaches to IT service provision, clients' involvement in the SDLC and the future of their services to improve operations in the agri-food and beverage industry. The presentation of the participating companies below highlights key facts about each and lists the participants from each company (where separate individuals held the roles).

Case study company profiles

To conduct in-depth interviews with industry specialists, the researcher follows the essential criterion that the participant must be operating in the agri-food and beverage industry. There are eleven participating case study companies: three are classified as large, with multiple interviews each, and eight are classified as small, with one interview each. The twelfth participant is an IT service provider who helps the researcher make sense of the industry and the BDA element of MCS. The IT company is not a case study; rather, it is considered an expert informant (Wasco, Campbell and Clark, 2002; Tongco, 2007; Handford and Matous, 2011).

All participating companies are situated in Ireland, except for C10, which is based in the UK (Northern Ireland). C1-3 are large companies, and three participants were available for interviews, as each of the three target roles is held by distinct persons.

C4, C6, and C7 are smaller companies; hence, the financial controller performs the functions of a management accountant and an IT manager, and only one interview was conducted. For C8-C10, the CEO is responsible for executing the responsibilities associated with the three functions. C11 and C12 are large enough, but there is no dedicated management accountant role. So, the financial controller incorporates the management accounting function. Hence, for C11 and C12, the financial controller and IT manager were interviewed. C5 is an IT provider which acts as an expert informant, as explained earlier. The following (Table 2) captures basic information about the participating case-study companies and the interviews conducted. Company size is based on EU categorisation by employee numbers: Micro (<10), Small (<50), Medium (<250), and Large (>250). C10 has just above 250 employees, thus classified as medium-large.

Table 2: Participating case companies' profiles

Case ID	Main business	Size	Age	Interviewee Role(s)	Duration (All interviews)	Date collected
C1	Meat processing	Large	1985	FC/MA/IT Manager	120 mins	Jul 2022
C2	Potato crisp production	Large	200+ years	FC/MA/IT Manager	128 mins	Aug 2022
C3	Chocolate production	Medium	1992	FC/MA/IT Manager	105 mins	Feb 2023
C4	Dairy	Large	1997	Financial Controller	48 mins	Jul 2022
C5	IT service provider	Micro	2005	CEO	49 mins	Dec 2022
C6	Dairy	Medium	1990	Financial Controller	42 mins	Jan 2023
C7	Meat processing	Large	1954	Financial Controller	25 mins	Jul 2023

C8	Meat processing	Medium	2008	CEO	45 mins	Oct 2023
C9	Meat processing	Medium	1965	CEO	43 mins	Oct 2023
C10	Pet food manufacturer	Med-Large	1972	CEO	23 mins	Feb 2024
C11	Bakery	Large	1897	FC/IT Manager	123 mins	Feb 2024
C12	Dairy	Large	1990	FC/IT Manager	58 mins	Feb 2024

In addition to the interviews, all participating companies granted the researcher permission to use information from their websites. The following information was extracted from the participants' websites, along with reasons for its extraction:

- **Quality and food safety:** Details HACCP plans, BRCGS certifications, and annual safety/quality review processes (e.g., audits, KPIs for defects, waste).
- **Operations/manufacturing:** Covers production controls, process optimisation, traceability, real-time monitoring, and yield/efficiency metrics.
- **Sustainability/ESG Reports:** Lists KPIs for waste reduction, energy use, supply chain audits, and performance dashboards tied to environmental and social goals.
- **Annual/integrated reports:** Includes governance of operations, internal audits, risk management, financial controls (budgeting, variance analysis), and continuous improvement processes.
- **Supply chain/procurement:** Describes supplier audits, quality gates, cost controls, and traceability from farm to factory.
- **Technology/digital transformation:** Mentions automation, data analytics, and integrated control platforms for compliance and efficiency.

The information was captured in text format and uploaded to NVivo for analysis alongside the interview transcripts. The text is coded in the same way as the transcripts to capture participants' MCS strategies and the extent to which BDA is being embraced.

5.4.4 Semi-structured Interviews

Qualitative approaches capture rich, context-specific information, facilitating an understanding of stakeholders' subjective experiences and perceptions (Bryman, 2015). Qualitative methods, like semi-structured interviews, provide the necessary flexibility to investigate the complex nature of research questions (Creswell and Creswell, 2018). Numerous studies regarding technology usage in organisations have employed a consistent research methodology, characterised by exploratory qualitative approaches utilising semi-structured interviews (van Kessel *et al.*, 2014; Mikalef *et al.*, 2019; Sheng, Amankwah-Amoah and Wang, 2019). Adams (2015) describes semi-structured interviews as a data collection method in which the researcher employs both closed- and open-ended questions, often accompanied by follow-up “why” or “how” questions. Semi-structured interviews are valuable in qualitative research because they offer a flexible and contextually rich approach to data collection (Roulston, 2008). They balance structured and unstructured approaches, thus providing a basic framework of questions and topics to be covered while allowing the interviewer to adapt and explore new avenues based on the participant’s responses. This approach to data collection creates a degree of flexibility which enables the researcher to gather rich, in-depth data that might not emerge in highly structured interviews (Knott *et al.*, 2022). This approach thus enables researchers to explore complex, diverse, and nuanced phenomena while allowing for iterative research design and ethical considerations (Wang *et al.*, 2025). This flexible approach balances structured and unstructured data collection methods.

The vast array of products offered in the agribusiness industry implies that each agrifood and beverage manufacturing company may have different processes that generate various data. Companies in this industry use a variety of machinery to collect and analyse data, which is turned into information. Due to the complexity of manufacturing processes in this industry, semi-structured interviews are well-suited to an iterative research design that allows the researcher to modify their interview guide based on emerging findings. This approach enables the researcher to examine the manufacturing process to understand their data-capture and analysis techniques. The flexibility in this approach enables researchers to gather rich, in-depth data that might not emerge in highly structured interviews (Collins *et al.*, 2019; El-Haddadeh, 2020;

Trevisan and Formentini, 2024). Technology implementation often involves multiple factors, like the individual's ability and the quality of the technology piece itself. Thus, semi-structured interviews allow researchers to investigate participants' experiences, perspectives, and emotions in depth (Virtanen, Tuomaala and Pentti, 2013; Duan, Edwards and Dwivedi, 2019; Konou *et al.*, 2025). By following up on responses and asking open-ended questions, researchers can uncover nuanced information and gain a comprehensive understanding of the success or failure story behind the implementation of BDA in the agri-food and beverage industry.

Qualitative researchers invest in attracting participants who possess the most relevant characteristics to the study (Suzuki *et al.*, 2007). This approach often yields a purposive sample, a representative subgroup of a larger group designed to serve a specific need or purpose. In this case, the purposive sample was considered from two perspectives: the companies of choice and the individuals to be interviewed within them.

Data saturation, defined as 'information redundancy' or the point at which no new themes or codes 'emerge' from data, is widely referenced in thematic analysis (TA) research in sport and exercise and beyond (Braun and Clarke, 2021c). Data saturation may be used in qualitative research as a criterion for discontinuing data collection and/or analysis (Saunders, Lewis and Thornhill, 2023). They argue that saturation should be operationalised in a way consistent with the research question, theoretical position and the analytical framework.

Braun and Clarke (2021a) argue that although the concepts of data-, thematic- or codesaturation, and even meaning-saturation are coherent with the neo-positivist, discovery-oriented, meaning excavation project of coding reliability types of TA, they are not consistent with the values and assumptions of reflexive TA.

To gather data from interview subjects that would answer the study's research questions, a semi-structured interview schedule was developed. This approach was judged most appropriate for this study because it would allow interviewees to share their ideas while guiding them in discussing theoretically significant topics. Once

participants agreed to participate in the study, they were provided with background information through a participant information sheet and a consent form, which they were required to sign and return to the researcher. This process was followed by providing the participants with an interview guide, which consisted mainly of a list of themes or general topics on which the questions would be phrased to answer the research question. Kallio et al. (2016) recommended using an interview guide as it offers a focused structure for the discussion during the interviews, but should not be followed strictly (Fossey *et al.*, 2002).

Moreover, the interview guide provides the opportunity to explore the research area by collecting similar types of information from each participant. This approach allows the researcher to pursue specific themes or questions in greater detail and address any new areas as they emerge during the interview (Adams, 2015). The interviews used an interview guide with illustrative questions (Appendix E – Interview Questions) while acknowledging that participants' responses may add previously planned questions. Although all the interviews were conducted based on the guide (thus, the same themes or topics), the researcher may adapt the formulation of the probe questions, including the terminology, to fit the background and knowledge level of the participants (Patton, 2014). The order in which the topics are discussed may also vary depending on how the interview develops. Yin (2018) portrays a semi-structured interview as more of a guided conversation than a structured enquiry.

The interview was divided into four sections:

Theme 1: Big data in context, where the aim was to reaffirm the use of big data in the case study organisation. This theme aims to clarify the roles and responsibilities of participants, enabling them to align their responses with their expected knowledge of the matter under investigation. This theme is also geared at identifying the accounting software system used within the organisation, building a picture of a strategic fit, or identifying alternatives. Finally, questions under this theme aim to establish the participants' definition and awareness of what constitutes big data and how it applies to their organisation.

Theme 2: How does BDA affect the core role of management control? The questions under this theme were posed to assess the impact of data analytics on manufacturing process efficiency in agri-food and beverage companies. Additionally, the theme aims to explore other applications of big data in agri-food and beverage companies.

Theme 3: How does the MCS structure influence the need for BDA technologies? This theme aims to establish management controls that utilise data analytics to ensure their effectiveness. These include the core values of the organisation (vision and mission statements, organisational structure), risks to avoid, critical performance variables (KPIs), strategic uncertainties (Brexit, Covid-19, Russia-Ukraine war, etc.), and their impacts on the supply chain, labour force, and sales.

Theme 4: Barriers to effective use of BDA in MCS. As with any technological advances, this theme seeks to identify challenges that limit the organisation's ability to maximise the use of BDA to facilitate MCS.

Based on the interview guide, the researcher designed the questions for this study to explore different themes and concepts, all linked to the research question, in plain English. The questions under the second theme varied depending on the interviewee's background and expertise, as highlighted in the answers to questions under the first theme. The interviews were conducted via Microsoft Teams, which can record both text and video. As an online tool, interviewing via MS Teams eliminates the need for travel, saves time, and makes scheduling interviews at convenient times for researchers and participants. Text and video recordings worked effectively at the transcription stage, as lip reading helped identify challenging comments that would have been impossible to transcribe without re-interviewing the participants. Each interview lasted between 23 and 49 minutes (45 minutes on average). The interviews began with the researcher presenting background information on the research project to the participants, summarising information from the information sheet given earlier. This initial encapsulation of the research project refreshed the participants' minds, allowing them to feel free to disclose as much information as possible. This explanation was followed by the first question, which prompted them to discuss their role within the organisation and the responsibilities assigned to them. Their response to this question

helped establish the general activities associated with their authority level on the research topic. The remaining questions were phrased to allow participants to narrate their activities, yielding the data required for this study.

5.4.5 Data Triangulation

Turner and Turner (2009) define triangulation as an alternate perspective to validate, challenge or extend existing findings. One of the key contentions in doing case study research has been the issue of rigour (Gibbert, 2008; Gioia et al., 2013; Grodal et al., 2020), and various types of triangulations exist. At least four possible types of triangulation have been identified, including (1) data source triangulation, (2) analyst/investigator triangulation, (3) theory/perspective triangulation, and (4) methods triangulation (Arksey and Knight, 2011; Yin, 2013; Layder, 2019). Yin (2013) further asserts that of these four triangulation methods, data sources and methods, in particular, are likely to strengthen the validity of a case study evaluation. For this study, triangulation is achieved by employing a variety of data sources, particularly semi-structured interviews and document reviews. Using different data sources, distinct from using different methods in data production, is referred to as data triangulation (Arksey and Knight, 2011) and has been employed in similar studies (Aureli *et al.*, 2018; Feeney and Pierce, 2018).

Yin (2014) identifies interviews as one of the most important sources of case study information and recommends that they be guided conversations rather than structured queries. Primary data for this study were collected using interviews, as they tend to focus directly on the case study topics and provide perceived causal influences and explanations (Yin, 2018). Although interviews can be biased, using semi-structured interviews ensures that the actual stream of interview questions in this case study was likely fluid rather than rigid while pursuing a consistent line of inquiry. The secondary data came from reviewing the documentation (from participating companies' websites and documents from BDA service providers). Yin (2018) considers documentation an important source of evidence because it is stable, unobstructed, exact, and provides broad coverage. Essentially, documents can be reviewed repeatedly, not created due to the case study, contain exact names, references, and event details, and span long periods, many events, and many settings.

5.4.6 Quality and Rigour Assurance

The subjective nature of the data, the difficulties in communicating with participants, and the rigour required for accurate and trustworthy results are frequently significant obstacles in qualitative research. Close interaction with participants is a key component of qualitative research, and researchers must be continuously reflective to prevent their own opinions or feelings from influencing the findings. The researcher's role and positionality can significantly impact the quality and rigour of assurance that the data has been collected and analysed without bias. The following few paragraphs highlight the researcher's role and positionality in relation to the study, as well as the ethical considerations involved.

Role of the Researcher

Creswell (2018) suggests that a researcher's background, views and experiences must be clearly and explicitly stated in a qualitative study. In qualitative research, the role of the researcher is central to every phase of the study, as they are the primary instrument of data collection and analysis. Their responsibilities go beyond mere observation; they actively engage with participants, interpret data, and ensure the ethical integrity of the research. In addition to being a passive observer, the researcher collaborates with participants to produce profound, complex understandings of social processes and human experiences (Carcary and College, 2020). Some key attributes of a researcher include their involvement in this approach, such as reflexivity, ethical consciousness, and adaptability to changing study environments. These requirements are shaped by the researcher's life experiences. The first step in accomplishing the reflexivity aspect was to apply for ethics clearance to the university's ethics committee, which ensures that the researcher can conduct the research in accordance with the university's ethical rules.

Beyond the university's ethical rules, the researcher assumes an epistemological position prior to collecting and analysing the data that support the research question's answer. Epistemological assumptions influence the researcher's positionality regarding representation and truth, the researcher's role and power relations with others, and the criteria for evaluating qualitative research (Corlett and Mavin, 2018).

Corlett and Mavin (2018) also encourage the researcher to see the value of reflexivity in its ability to bring epistemological, methodological, and critical challenges to the forefront as a means of acknowledging how, through their researcher positionality and as qualitative researchers, they influence the research they conduct and shape the knowledge they produce. In the next section, a detailed articulation of the researcher's experience and their ability to gather data to establish how BDA can facilitate MCS is presented by examining their positionality. England (1994) defines positionality as a position based on class, gender, race, etc., and on the researcher's biography, which plays a central role in the research process. To shed light on the researcher's positionality, the following section employs a first-person writing style to portray the researcher's self-reflection.

Researcher Positionality

Following my initial training as a secondary school teacher, I taught mathematics for several years before retraining as a software developer. I then worked on various projects, ranging from quote-generation systems for mining-equipment maintenance companies to school-record maintenance systems. Most of my career in the software industry revolved around projects that developed financial systems packages. The highlights include leading a team to migrate South African ABSA Bank's database to Microsoft SQL Server (SQL 7) and using OLAP tools introduced in this version of SQL Server to perform online tasks such as creating, maintaining, and closing bank accounts. At the peak of my career in the software industry, I led a team of programmers to develop a comprehensive software package to manage the Chadian government's social insurance system. For this project, I held the dual role of project manager and system analyst, ensuring that the system requirements met the client's needs, were delivered on time, and remained within budget.

At this stage in my career, I had been exposed to many business principles; thus, deciding to change my career path led me to study accounting. After completing a master's degree in professional accounting, I trained to become a member of the CPA Ireland. Soon after, my teaching instinct brought me back to academia, so I embarked on the PhD journey that led to this research. My life experiences and interest in emerging technologies have guided my choice of research area. During my training to become a member of CPA Ireland, I worked for a pharmaceutical company in Dublin.

I was intrigued by how they maintained, analysed, and used their financial records. Based on my experience in the IT industry, I introduced some tweaks to their spreadsheet use (Microsoft Excel), which my colleagues in the accounting department embraced.

My inquisitiveness was sparked by the question of whether organisations are utilising the technology at their disposal. Therefore, I thought it necessary to explore how organisations utilise technology, especially emerging technologies that require some time to master. If spreadsheets that have existed since the 1980s could still be underused, what more of emerging technologies? During my early literature review of IT technologies, I found many studies evaluating the value-for-money invested in IT systems. However, limited attention has been paid to the extent to which these systems' full functionality is used. I approach this study from an ontological perspective informed by post-positivism because I believe that multiple factors influence the effective use of technologies such as BDA. However, the software system might have been developed succinctly; factors such as the user's ability to understand how to use it may lead to underuse. This challenge is even more severe with emerging technologies, as they evolve faster than users' ability to learn how to use them. Most of the applications I have been involved in developing would be classified as bespoke applications, developed for a specific client with specific tasks in mind. We often provide training as part of the package, yet users still find it challenging to utilise the systems to their maximum potential. BDA technologies and tools like Hadoop, Tableau, and Power BI can be challenging to implement. Also, as with any on-the-shelf system, it is customisable, but it also poses the challenge of using all its functionalities. I am interested in determining the extent to which BDA is used to facilitate MCS and identifying the challenges that arise thereafter.

Although this is not participatory research, my interpretation of the participants' statements is influenced by my own experience and expectations. Having worked in the IT industry as a software developer, I am always eager to provide solutions to issues that can be resolved using computer software. BDA technologies provide solutions to manufacturing issues when properly applied. At the beginning of the study, I was exposed to a vast body of literature that shed some light on the issues in the manufacturing industry. In this regard, I made every effort not to draw any conclusions

considering the exact utterances of the participants. This precaution is reflected in the analysis section by including extracts from the interviews at various stages of the analysis.

The researcher admits that their background and opinions have unavoidably influenced their research project. By addressing potential alternatives, considering the implications of their well-informed decisions for research practice, being consistent in their actual interactions with management practices, and being explicit about how they satisfy particular but philosophically contingent evaluation criteria, researchers expose their philosophical presumptions to ongoing reflection and evaluation (Corlett and Mavin, 2018). The researcher took various steps to reduce subjectivity and potential study bias resulting from the use of this research tool. When conducting interviews, for instance, care was taken to ensure that the researcher's opinion was not shown through the questions (Johnson, Adkins and Chauvin, 2020), like in wording, emotions, reactions, and so on. Ethics and other considerations have also supported this precaution to ensure that rigour assurance is enforced as effectively as possible.

Ethics and Other Considerations

The emergence of Human-Computer Interaction (HCI) was driven by the shortcomings of existing approaches in adequately describing and understanding how people interact with a new breed of pervasive digital technologies in everyday life (Frauenberger et al., 2016). This challenge has become more prominent today as organisations increasingly incorporate internal and external data sources into planning, control and decision-making, requiring plans, policies and procedures to ensure legal and ethical compliance (Rikhardsson and Yigitbasioglu, 2018). Management must adhere to legal and ethical guidelines when obtaining and using data. In addition to these challenges already faced by managers, this research needed access to information on business operations, some of which might have been competitively sensitive. Management could therefore be apprehensive about answering questions that seemed sensitive to the business, thereby presenting an ethical dilemma that the researcher had to resolve.

Townsend and Wallace (2016) point out that an ethical approach should be taken to collect, analyse, and reuse data, especially when the data is potentially sensitive. Organisations are more likely to cooperate if those involved see the research objectives as valuable and relevant (Ritchie and Lewis, 2003) and if the research will not infringe on their rights to confidentiality. While formal ethics procedures are important safeguards and support researchers in planning their work, drawing on Frauenberger et al. (2016), they are insufficient to address the ethical dimensions that emerge from a situated understanding of the human-computer interface, with its epistemological and methodological consequences. Approval of research with individuals or groups may also be required from an ethics committee, particularly, but not exclusively, if the research involves sampling from or contact with sensitive information (Buchanan and Hvizdak, 2009). In this respect, ethical approval was sought from the university, and data collection was only commenced once it was received. Also, organisations were provided with information and explanations to assure them of the benefit and value they would accrue from the research.

5.5 Data Analysis

Despite its unfamiliarity with statistical abstractions, qualitative research employs a systematic approach to data gathering and analysis. Gathering data through interviews, open-ended questions allow research participants to freely and spontaneously express their perceptions and experiences in the area. When examining data produced this way, responses are not categorised using pre-established categories; instead, key meaning groups and their connections are inferred from the data using inductive reasoning techniques.

In abductive research, a researcher starts with specific procedures to collect data and then develops general conclusions or theories based on that data. The researcher collects data, observes patterns, and identifies themes or categories that emerge from the data (Williams, 2007). They then develop a theory or explanation for the patterns observed. SST provides a comprehensive framework for analysing thematic data to understand both existing and new knowledge. As stated above, inductive researchers use a series of empirical cases to identify a pattern from which to make a general

statement; thus, inductive logic consists of inferring categories or conclusions based on data (Kennedy and Thornberg, 2018).

This research aims to investigate how BDA facilitates MCS, as MCS heavily relies on efficient information. SST connect these two concepts by identifying the mediating factors that ensure their successful implementation. The social world can be seen as the outcome of human decisions using the information and resources available. BDA technologies are crucial in reaching targets set by various KPIs and revealing new insights that could push incredible innovation (Liu, Chen and Liu, 2020; Braglia *et al.*, 2022).

This section begins with a detailed explanation of the analytical strategy used for this study: thematic analysis. A thematic data analysis approach organises and simplifies complex data into meaningful, manageable codes, categories, and themes (Kalpokaite and Radivojevic, 2019). This approach provides an audit trail of the coding and analysis that led to the conclusions reached in this study.

5.5.1 Data Analysis: Techniques and Procedures

Thematic analysis is a ‘best fit’ for this study, compared with other qualitative analysis strategies such as grounded theory, interpretive phenomenological analysis, and discourse analysis (Eisenhardt and Graebner, 2007; Creswell and Poth, 2018; Yin, 2018; Braun and Clarke, 2022b). The thematic approach allows the use of excerpts and quotes from interview transcripts and reviewed documents to align with the identified themes, thereby relating the data to the research question (Castleberry and Nolen, 2018). Braun et al. (2014) argue that thematic analysis can be applied across a philosophical paradigm, consistent with an interpretivist stance. The abductive nature of this study necessitates such an approach to compare the findings with the existing literature, as presented in the integrated framework for the design and use of MCS using BDA. The iterative discussion of empirical findings and theoretical literature culminates in the presentation of an evidence-based framework that will continue to enhance the knowledge base for researchers and organisational strategists, paving the way for achieving maximum output from BDA.

The key principles of thematic analysis are grounded in interpreting and making sense of data by identifying patterns, themes, and concepts that emerge from the data. The researcher has followed a clear and structured process for analysing the data and documenting their decisions and reasoning, critically reflecting on their assumptions, biases, and perspectives and how these might influence their interpretation of the data and remaining open to unexpected or divergent findings that may challenge or enrich their initial assumptions (Kalpokaite and Radivojevic, 2019). Finding patterns, themes, and concepts is the three main guiding principles of the analytical process, described below.

5.5.2 Analytical Process: Phases and Steps

The successful examination of interview data began with categorising participant replies by meaning rather than pre-defined categories, followed by employing inductive reasoning to derive connections between the categories. Qualitative approaches are incredibly diverse, complex and nuanced; hence, Braun and Clarke (2021b) suggest thematic analysis as the primary method for qualitative analysis. The thematic analysis approach enabled me to examine articulated views and incorporate them into a model that aims to explain the social processes under investigation (Braun and Clarke, 2021b). Thematic analysis is a method for identifying, analysing and reporting patterns (themes) within data (Braun and Clarke, 2006). Braun and Clarke (2006: 78) also suggest that “through its theoretical freedom, thematic analysis provides a flexible and useful research tool, which can potentially provide a rich and detailed, yet complex, account of data”. The approach to thematic analysis takes its roots from its independence from any particular epistemological and ontological base, and this ‘flexibility’ is partly what makes it distinct from other qualitative analyses (Terry *et al.*, 2017). Thematic analysis is, therefore, deemed compatible with the interpretivism philosophy that this study has adopted (Braun and Clarke, 2021b). Some approaches to qualitative analysis are better described as methodologies, as they apply within particular theoretical frameworks, which inform the methods of data collection and analysis used within that approach (Terry *et al.*, 2017). Meanwhile, thematic analysis is widely applicable to a wide range of data sources, such as policy documents, field notes, interview transcripts, and observations (Herzog, Hitters and Handke, 2019), as it is not limited to any particular study methodology (Terry *et al.*, 2017).

Thematic analysis is a popular technique for analysing qualitative data, helping researchers find and examine patterns and themes in their data. Identifying, analysing, and reporting patterns in data is integral to this adaptable, iterative process. One of the most widely used approaches to conducting thematic analysis is the process proposed by Braun and Clarke (2006). This section provides a thorough explanation of the Braun and Clarke thematic analysis procedure, as applicable to this study.

Having outlined the methodological approach for this study, I now turn to the empirical material itself. This section constructs a detailed analytical narrative of the cases. The analysis proceeded in six stages. The stages are iterative, providing the required flexibility, complexity and structure for researchers to scrutinise comprehensively and interpret the qualitative data systematically (Peel, 2020). These phases included (1) familiarisation with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the report (Braun and Clarke, 2006). During these phases, there are multiple coding cycles, code management, categorisation, and data reduction by consolidating codes into a more abstract theoretical framework (themes) while using writing as a reporting tool to encourage deeper data analysis (Peel, 2020), leading to the findings presented in this study. During this process, I first developed a comprehensive analytical narrative that synthesised the coded data (stages 1 and 2). Secondly, I interpreted this narrative in relation to the theoretical framework and research questions (stages 3-6). Finally, I translated these interpretations into the empirical findings (Chapter 6) and the subsequent discussion (Chapter 7).

Central to Braun and Clarke's (2006) thematic analysis is its flexibility, which makes it applicable to both inductive and abductive research designs. The technique's flexibility presents the challenge of accurately matching different approaches with diverging philosophies. Another explanation for this challenge is that since inductive reasoning often goes from specific observations to general principles (theory building), the results obtained from this approach may not be as specific as those obtained from abductive reasoning, which starts with a broad theory and uses it to make specific predictions or testable hypotheses. However, Thompson (2022) suggests that the researcher's engagement with the process and transparency about the analytical steps taken could reduce this limitation. The researcher's responsibility is a key requirement

of the abductive approach to theory development, an approach employed in this study. Thomas (2006) summarises the purposes underlying the development of the general abductive analysis approach as follows:

1. to condense extensive and varied raw text data into a summary format;
2. to establish clear links between the research objectives and the summary findings derived from the raw data and to ensure that these links are both transparent (able to be demonstrated to others) and defensible (justifiable given the objectives of the research); and
3. to develop a model or theory about the underlying structure of experiences or processes that are evident

Guided by Braun and Clarke's (2019) extensive literature on the thematic analytical approach, the researcher endeavoured to accomplish all the goals of abductive inquiry by synthesising themes that are analytical products derived from the researcher's creative labour (Braun and Clarke, 2019). The entire process began with transcribing the interview recordings into readable text, followed by a detailed analysis to identify relevant themes that will inform the development of a framework, the ultimate objective of this study. By adopting this approach, the results reflect considerable analytic 'effort' with the researcher actively bridging the intersection of data with the analytic process while 'minimising' subjectivity (Terry *et al.*, 2017). The essence of the thematic analytical process is to develop themes to generate a report. Themes are imaginative, interpretive narratives about the data generated by the interaction among the data, the researcher's theoretical presumptions, and their analytical tools and abilities. Consequently, the researcher's subjectivity is integral to the analysis process (Braun and Clarke, 2022a).

In addition, Braun and Clarke (2006) point out that researchers develop themes around two 'levels' identified as a semantic or explicit level or a latent or interpretative level. A thematic analysis typically focuses exclusively or primarily on one level, without looking beyond what a participant has said or written (Braun and Clarke, 2006). They further contrast thematic analysis at the latent level, go beyond the semantic content of the data, and begin to identify and examine the underlying ideas, assumptions, conceptualisations, and ideologies theorised as shaping or informing the semantic

content. The latter stance captures the researcher's subjective role in delving deeper into the data to uncover latent themes. “Abductive analysis is, therefore, a process of coding the data without trying to fit it into a pre-existing coding frame or the researcher’s analytic preconceptions” (Braun and Clarke, 2006: 83). The researcher’s relationship with the data was not static but fluctuated constantly: shifting back and forth along a continuum of possibilities, from one moment to the next, from one location to the next, from one interaction to the next, and even from one discussion topic to the next (Mercer, 2007). Similarly, the researcher moved back and forth recursively between coding and theme development, leading to new interpretations of the data that may necessitate further iterations of earlier phases (Byrne, 2022). Braun and Clarke (2021) specifically developed thematic analysis as an approach embedded within and reflecting the values and sensibilities of a qualitative paradigm, to distinguish it from positivist quantitative paradigms that prioritise objectivity and the reliability of observation. They dubbed this approach “reflexive thematic analysis” to reflect their view of qualitative research as creative, reflexive, and subjective, with the researcher's subjectivity deemed a valuable resource. Researchers employing reflexive thematic analysis may become bound by data saturation, limiting the uncovering of new ideas, yet saturation may be explored or imagined differently (Braun and Clarke, 2021c).

In addition to the challenges posed by the subjectivity of the resulting themes, the issue of data saturation has drawn the attention of many scholars. However, Braun and Clarke (2021: 9) argue that data saturation might be challenging to align with thematic analysis in that:

Coding quality in thematic analysis stems from the depth of engagement with the data and situated reflexive interpretation. This process-based, organic, evolving orientation to coding makes saturation (primarily conceptualised as information redundancy) difficult to align with.

Achieving saturation in abductive qualitative research involves reaching a point where new data or interviews no longer yield additional insights relevant to the research questions or themes. Saturation indicates that the researcher has comprehensively explored the topic and that further data collection is unlikely to yield substantially new information. As saturation is a continuous process, I frequently analysed data in

parallel with the interviews. Saturation was reached when the analysis indicated that additional interviews no longer yielded new insights. Deeper analysis and coding do not always lead to the same result. Instead, to finalise the written report, I made a situated, interpretative decision regarding when to stop coding and begin theme generation, as well as when to stop theme generation and map thematic relationships (Braun and Clarke, 2021c). The concept of "saturation" for thematic analysis researchers could be an interpretive determination regarding the objectives and purpose of the analysis, similar to Low's (2019) reinterpretation of theoretical saturation in grounded theory as "pragmatic saturation". This study adheres to the recommendations of Braun and Clarke (2021) regarding data saturation and thematic analysis, while building upon the principles of thematic analysis outlined in their 2006 work. The study considers saturation to be the point at which no new themes or insights emerge, rather than a predetermined number of interviews. To this end, interviews were transcribed and analysed in stages, with the number of interviews increasing as needed.

Throughout the coding process, I did not take my attention off the role SST plays. SST assisted with thematic analysis by providing a structured lens for coding data, ensuring that themes capture the dynamic relationships among actors, structures, and practices rather than simply describing organisational behaviour (Giddens, 1984; Jack and Kholeif, 2008; Englund, Gerdin and Burns, 2011). SST informed the coding process by providing sensitising concepts that guided the identification and interpretation of themes. In particular, the quadripartite framework (external structures, internal structures, active agency, and outcomes) helped organise codes and link individual actions with broader organisational and industry contexts.

The rigorous six-stage data collection and thematic analysis process outlined and elaborated below, (Table 3) underpins the robustness and effectiveness of the overall data analysis. These six phases are not rules and must be applied flexibly to fit the research questions and data. Braun and Clarke (2006) point out that analysis is not a linear process of simply moving from one phase to the next; instead, it is a recursive process, with movement back and forth across the phases as needed.

Table 3: Phases of thematic analysis[adapted from (Bonello and Meehan, 2019; Braun and Clarke, 2006)]

ANALYTICAL PROCESS	STRATEGIC OBJECTIVE	KEY ACTIVITIES	PRACTICAL APPLICATION IN NVIVO
1. FAMILIARISATION WITH THE DATA	Gain a deep understanding of the data and the context	Immerse in the data through repeated reading or listening. Note initial thoughts and ideas.	Open coding ➤ Import and organise data in NVivo ➤ Annotate and memo data for better understanding. ➤ Use NVivo to create codes for different themes. ➤ Code relevant portions of data to capture key concepts.
2. GENERATING INITIAL CODES	Systematically coding interesting features of the data.	Systematically code meaningful data units: Generate labels (codes) for identified patterns.	
3. SEARCHING FOR THEMES	Organising codes into potential themes.	Collate codes to identify potential themes: Group related codes to form broader patterns.	Axial coding ➤ Utilise NVivo to cluster related codes into axial codes. ➤ Explore relationships between codes using NVivo tools. ➤ Axial codes become categories.
4. REVIEWING THEMES	Refine and define themes by checking against the data.	Check themes against the coded data for accuracy: Refine and modify themes as needed.	Developing themes ➤ Cross-reference coded data with sources in NVivo.

5. DEFINING AND NAMING THEMES	Clearly defining what each theme represents.	Develop clear definitions for each theme: Provide concise and descriptive names for themes.	● Identify and resolve discrepancies in coding. ● Create detailed descriptions for each theme in NVivo. ● Assign appropriate names to themes based on their essence.
6. WRITING THE REPORT	Presenting the findings coherently and convincingly.	Develop a narrative that integrates themes: Support themes with illustrative quotes/examples.	● Use NVivo to retrieve coded segments and support findings. ● Export relevant data and visualisations for inclusion in the report.

Qualitative data analysis is a complex process that requires meticulous attention to detail and a systematic approach. As stated above, this study uses the Braun and Clarke thematic analysis approach to ensure the reliability of the results. Software tools, such as NVivo, can facilitate this process by providing researchers with tools to easily manage and analyse data.

NVivo is a Computer-assisted (or aided) qualitative data analysis software CAQDAS developed by QSR International to help researchers analyse unstructured or qualitative data. Its features, including data management, coding, querying, visualisation, and collaboration, make it a versatile tool used in various research contexts. Braun and Clarke's thematic analytical approach integrates seamlessly with NVivo, thereby providing a dual tool for analysing this study more robustly. It is important to emphasise that when a researcher uses software for qualitative data analysis, they do not submit the interpretation work to the computer's logic. Instead, the computer is an efficient tool rather than a tool that analyses and draws conclusions. In the words of Fielding and Lee (1998: 167), qualitative researchers “*want tools which support analysis, but leave the analyst firmly in charge*”. Sinkovics and Alfoldi (2012) argue

that, rather than trying to constrain or conceal the fluid and often serendipitous nature of their work, qualitative researchers would do well to turn to CAQDAS to manage and document the research process more effectively. They go on to say that the skilful and systematic application of CAQDAS can also aid in creating an audit trail or chain of evidence that accurately reflects the steps involved in data analysis, including organising and categorising the data, looking for patterns, continuously comparing the results with theory, and modelling an emergent framework. All phases of the analytical process are traceable and transparent thanks to qualitative analysis software's ability to log data movements, coding patterns, the mapping of conceptual categories, and thought progression. The software enables researchers to create a more thorough audit trail (codebook) than would be possible through manual mapping of this intricate process. This study adopts a combination of a seasoned qualitative data analysis approach, such as Braun and Clarke, with a CAQDAS, such as NVivo, to facilitate the identification of themes from the interviews.

Based on Braun and Clarke (2006), Table 3 presents the six-step approach to conducting thematic analysis. The first column lists the processes (phases), while the second column briefly explains the strategic objectives of each phase. Column two illustrates the strategic coding elements as the researcher transitioned from initial participant-led descriptive coding to axial coding (more interpretive and involving both participant- and researcher-led approaches) to the final abstraction of themes (which is entirely researcher-led). The third column lists key activities and demonstrates the iterative nature of the tasks as the coding, analysis, and write-up proceed toward the conclusion. The last column provides a practical application of each phase using CAQDA software (NVivo). The use of NVivo illustrates the rigorous data analysis employed throughout this study, which is conducted as a recursive and iterative process. Phases one and two worked together to create the initial codes through repeated reading and re-reading. Similarly, the research combines phases four and five in NVivo to generate themes recursively. This movement from the primary data through the six phases of analysis ensured the generation of appropriate themes to answer the main research question of this study.

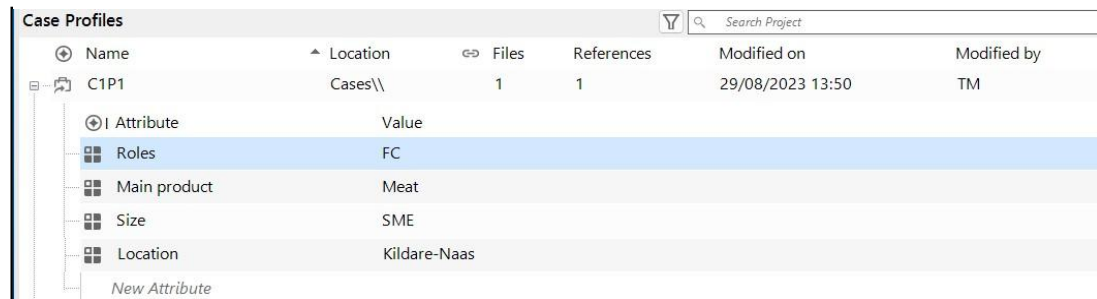
Phases 2-4 represent the actual coding process, which includes open coding (initial coding), axial coding, and theme development (selective coding). Open coding allows the researcher to begin generating thematic categories from qualitative data. In contrast, axial coding refines the categories by “reassembling the data fractured during open coding” and systematically linking and integrating categories and subcategories into more robust classifications of data (Ruona, 2005; Creswell and Poth, 2018). Each phase described below was carried out during the data analysis.

Participants’ role information is important in this study because they can transform or replicate the structures (agent-in-focus or agent-in-situ) through their use of BDA to facilitate MCS. The coding process hinges on SST, prompting me to capture what agents do in context and ground codes in observable practices rather than abstract opinions (Becker and Burke, 2012; Szymanski *et al.*, 2026). Hence, the Initial or open coding was embodied practices (focusing on quadrant 3 of the quadripartite framework). This approach yielded rich, agent-centred data. The axial coding phase links practices to conditions and knowledgeability, based on questions like “What rules/resources enable/constrain the agent’s use of BDA to facilitate MCS in this industry? The focus at this stage is on quadrants 1 and 2 of the quadripartite framework. For example, what do agents know/believe about regulations like HACCP (quadrant 1), or are managers sceptical of predictive models (quadrant 2)? Applying this judgement allowed me to prevent superficial coding by forcing connections between action and context. The final stages involved theme development, leading to emergent structures (quadrant 4). The cluster codes at this stage revealed duality, particularly in how practices are reproduced or structures are transformed, thus creating a clear link between quadrants 3 and 4. This final stage ensures themes are theoretically saturated, not just descriptive patterns (Roy *et al.*, 2015; Montealegre, Iyengar and Sweeney, 2019).

5.5.2.1 Phase 1: Familiarisation.

Before beginning qualitative data analysis in NVivo, it was important to set up a project, which involved creating folder structures to organise the data and nodes to categorise it. After importing the data, I organised it to facilitate analysis. This step involved creating cases and units of analysis in qualitative research. At this stage, I uploaded transcripts (progressively as each became available) and any associated

strategy documents (obtained from the participants' website) to NVivo. Gaining a deeper understanding of the topic required insight from multiple perspectives, as well as case nodes created in NVivo. Each case contained the entire interview of each participant, linked to their demographic and profile information, as illustrated in Figure 10.

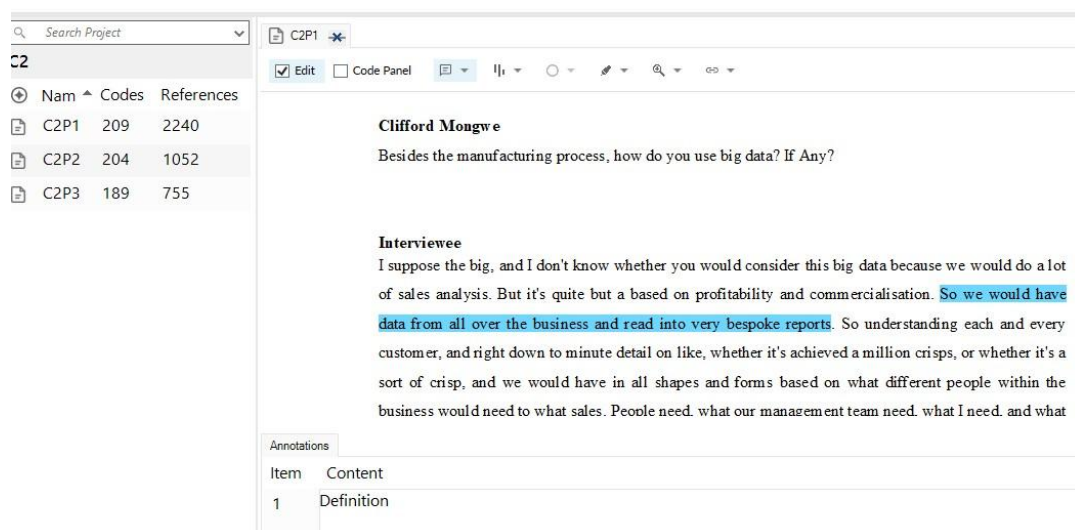


Name	Location	Files	References	Modified on	Modified by
C1P1	Cases\	1	1	29/08/2023 13:50	TM

Attribute	Value
Roles	FC
Main product	Meat
Size	SME
Location	Kildare-Naas

Figure 10: Setting up participants' profiles (source: NVivo data file)

NVivo enabled linking participants' profiles to the collected information, making it easier to retrieve and contextualise cases quickly. During this pre-coding stage, I explored the data and gained a global understanding by circling, highlighting, bolding, underlining, or colouring rich or significant segments of the data that capture their attention (Kalpokaite and Radivojevic, 2019). I used the highlight function in NVivo 14 to annotate text that initially captured my attention.



Nam	Codes	References
C2P1	209	2240
C2P2	204	1052
C2P3	189	755

Clifford Mongwe
Besides the manufacturing process, how do you use big data? If Any?

Interviewee
I suppose the big, and I don't know whether you would consider this big data because we would do a lot of sales analysis. But it's quite but a based on profitability and commercialisation. **So we would have data from all over the business and read into very bespoke reports.** So understanding each and every customer, and right down to minute detail on like, whether it's achieved a million crisps, or whether it's a sort of crisp, and we would have in all shapes and forms based on what different people within the business would need to what sales. People need. what our management team need. what I need. and what

Annotations

Item	Content
1	Definition

Figure 11: NVivo Case node [Source: NVivo extract]

For example, the definition of big data is likely an issue, as the concept is relatively new, and managers may not be fully aware of all the data sources in their industry.

5.5.2.2 Phase 2: Generating initial codes (Open coding)

The second step involved generating initial codes to identify and label patterns and themes as they emerged from the data. This phase involved broad participant-driven initial coding of sources in deconstructing the data from its original chronology into initial non-hierarchical general codes (Drisko, 1998; Ben, 2008). Coding is a fundamental step in qualitative data analysis, whether manually or by computer (Fielding and Lee, 1997), and involves labelling each unit of data within a data item (transcript or document) with a code that symbolises or summarises that extract's meaning (Saunders, Lewis and Thornhill, 2023).

While the entire research process, including data collection and transcription, inherently involves data condensation, the coding cycle places special emphasis on selecting, condensing, streamlining, abstracting, and/or changing the material that appears in the overall body of information (Kalpokaite and Radivojevic, 2019). Coding is not a one-directional process with a defined start and end point. According to Kalpokaite and Radivojevic (2019), coding is a process that requires numerous readings and re-evaluations of both the material and the actual codes created. Coding forms a crucial foundation in qualitative analysis, which is then developed into categories to identify themes, in line with Saldaña's (2013) suggestion that coding is not a precise science but rather a primarily interpretive act. The coding logic adopted in this study reflected this importance, thus going from the particular to the general, consistent with Saldaña (2013).

In the initial coding stage, data were extracted from their original textual context (interview transcripts) and organised into free codes, mostly descriptive and independent categories, with no apparent links or interconnections. Initial or open coding requires a close reading and interrogation of the data (Biles and Biles, 2010). I undertook the coding process to produce succinct, shorthand descriptive or interpretive labels for information relevant to the research question[s] (Byrne, 2022). After giving each significant statement a close inspection, I grouped them into themes

Data Extract	Potential category
We are always looking for those competitive advantages and brand advantages, and we're	Innovation

always looking to push and be different
 Figure 12: *Example of Data Extract and Code (so (C2P1) | Source: interview transcript)*

or meaning units (Roulston, 2008; Creswell and Poth, 2018). Since this study seeks to establish the use of BDA to facilitate MCS, it employed descriptive coding to document and categorise the breadth of opinions stated by multiple participants, as recommended by Saldaña (2013). Upon reviewing and reevaluating the data, the list of potential codes grew, and this recurring analytical step eventually encompasses the whole corpus of data (Braun and Clarke, 2013; Creswell, 2018). Figure 12 provides an example of data extracted linked to a potential code category.

At this point, I had completed the first coding of all 20 transcripts and had a sizable number of open codes. This process involved removing the data from the transcripts, which served as the original textual context, and categorising it into these free codes, which were broad, primarily descriptive, participant-driven, and stand-alone categories (units of meaning) devoid of any prominent linkages or connections. Due to the subjective nature of this process, I followed Maykut and Morehouse (1994) to provide a comprehensive "rule of inclusion" that described the criteria for including or excluding text segments for each free code.

Each free code was defined and detailed with a descriptive 'rule of inclusion', which outlined the basis for including or excluding text segments (Maykut and Morehouse, 1994). Each code label and description progressively generated a code list (codebook) from the identified extract. This phase involved preliminary line-by-line coding of all data sources and a description of each code, as illustrated in Table 4.

Table 4: Codes and Description - Initial Coding Process (Source: NVivo code extract)

Codes	Description
Challenges	Barriers to the implementation of big data analytics
Change Management	Managing resistance to change
Definition	What constitutes big data?
Innovation	Competition is a big challenge that innovation may help resolve.
Governance	Investment in IT - Authorisation process

KPIs	Contains references by participants to performance measurement or performance management
LOC-Belief	Defining the underlying principles of the organisation. What to expect from all employees
LOC-Boundary	Sets boundaries on the collection and use of data
LOC-Diagnostic	Belief and boundary systems may fail, and diagnostic control seeks to explain why.
LOC-Interactive	Interactions between departments should reduce uncertainty and increase innovation.
Processes	Improving process efficiency
Product Costing	Contains references by participants to "product costing"
Product Quality	Product quality controls
Risk Management	Covering a range of issues like preventive maintenance and compliance with FSA Ireland
Skills	Curriculum and skills gap analysis
Supply Chain	Supply chain management
System Quality	What makes a good accounting software system
Value Creation	Efficient use of resources
Visualisation	Presentation of information for decision-making

At this initial coding stage, I used annotations to indicate the code's potential relevance to the analysis. Annotations are important in qualitative data analysis, as everything is time and context-bound (Miles and Huberman, 1984). I used annotations to capture coding assumptions and ideas. These annotations were my comments and reflections on the text, capturing my thinking at that moment and reminding me of my thoughts at that time, as shown in the example below.

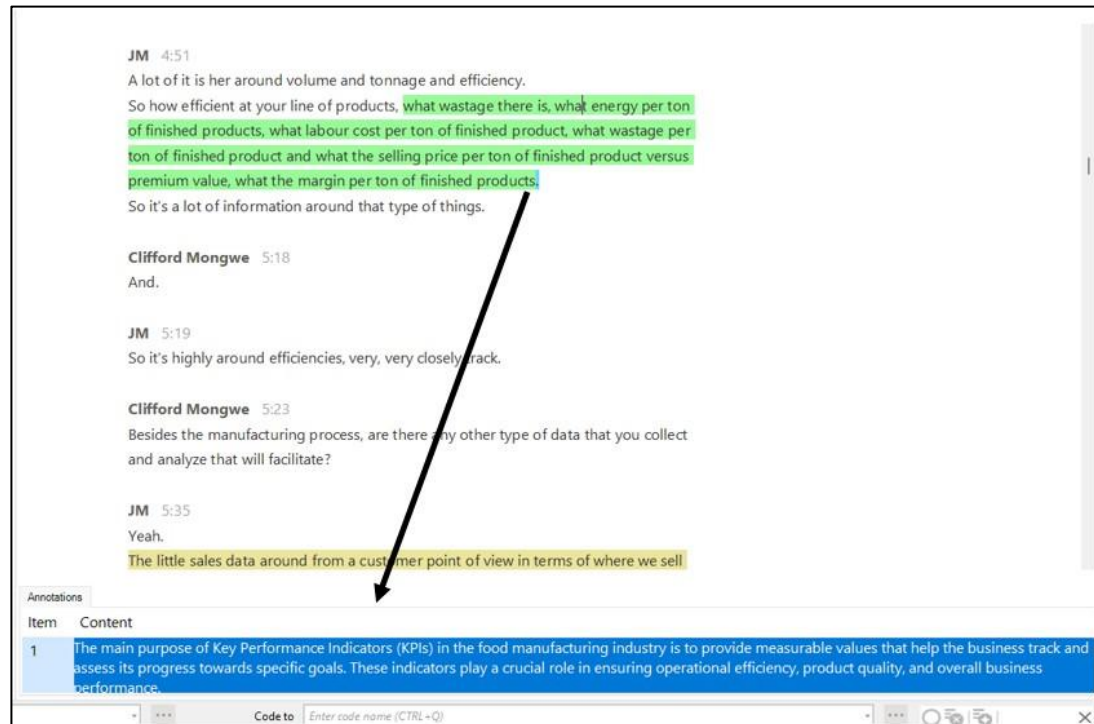


Figure 13: Example of annotation on a code snippet (Source: NVivo extract)

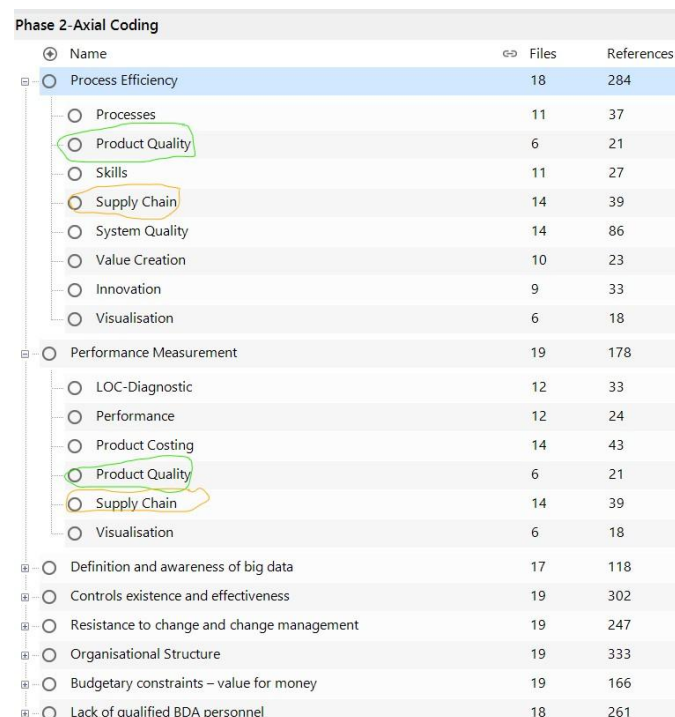
Free codes are free because they are non-hierarchical and not bound by the research question, but they allow for emergent themes to arise organically from the data (Bonello and Meehan, 2019). In the next phase, I began to assemble the free codes to identify potential themes that address the research questions.

5.5.2.3 Phase 3: Searching for themes (Axial coding)

This phase involved reordering the codes identified and coded in phase 2 into categories by grouping related codes under these categories (Creswell, 2018) and organising them to facilitate further analysis (Peel, 2020), guided by the research question. One way to think of categories is as a bridge between creating themes and logically grouping the original codes. This phase also included distilling, renaming, and merging categories to ensure that their definitions accurately reflected the coded content. A code category represents “a collection of similar data sorted into the same place, and this arrangement enables the researcher to identify and describe the characteristics of the category” (Morse, 2008: 727). At this point, I began to see patterns and ideas that kept emerging in the data, prompting me to consider these topics more abstractly. It was a repetitive procedure that involved enumerating important

concepts, taking notes, consulting the sources once more, and so on. Each new "unit of meaning" or text segment chosen for analysis is compared with all previous units of meaning and categorised and tagged with similar nodes in this nonlinear, iterative process. Through this method, I examined the data and identified patterns and contrasts, ultimately discerning the themes that captured its essence.

Through this largely intuitive coding process, I generated eight code categories representing popular KPIs within the agri-food and beverage industry that would likely benefit from implementing MCS using BDA. Figure 14 shows the eight code categories, with process efficiency expanded to reveal the codes that fall in this category.



Phase 2 - Axial Coding			
Name	Files	References	
Process Efficiency	18	284	
Processes	11	37	
Product Quality	6	21	
Skills	11	27	
Supply Chain	14	39	
System Quality	14	86	
Value Creation	10	23	
Innovation	9	33	
Visualisation	6	18	
Performance Measurement	19	178	
LOC-Diagnostic	12	33	
Performance	12	24	
Product Costing	14	43	
Product Quality	6	21	
Supply Chain	14	39	
Visualisation	6	18	
Definition and awareness of big data	17	118	
Controls existence and effectiveness	19	302	
Resistance to change and change management	19	247	
Organisational Structure	19	333	
Budgetary constraints – value for money	19	166	
Lack of qualified BDA personnel	18	261	

Figure 14: Developing categories - Axial coding (Source: NVivo extract)

Each of these codes contributes to process efficiency or enables its measurement. For example, the design of a manufacturing process determines its effectiveness, while visualisation techniques enable evaluation of that effectiveness. Each category contains codes that support the categories, but some codes may affect more than one category. Product quality and supply chain management codes affect process efficiency and performance management categories. A combination of categories culminated in themes which aim to answer the research question.

5.5.2.4 Phase 4: Reviewing Themes (Developing themes)

To provide a more thorough understanding of the highly qualitative aspects under examination, I divided the now-restructured categories into subcategories, considering various viewpoints and perspectives coded to these categories, providing clearer insights into the meanings entrenched in the data. During this phase, I began to recognise recurring themes and ideas in the data; thus, I began thinking about them more abstractly. Braun and Clarke (2022) figuratively express the researcher's responsibility to develop themes from data analytically. Themes are conceptualised (implicitly) as “fossils hidden in a rock” or “diamonds scattered in the sand”, lurking in the data awaiting “discovery” by the researcher. They further characterise themes as patterns of meaning anchored by a shared idea or concept (the central organising concept), rather than summaries of meaning related to a topic. Therefore, a theme is a broad category that encompasses several codes that appear to be related (Saunders et al., 2016). Though construing the importance or salience of a theme is not contingent upon the number of codes or data items that inform a particular theme (Byrne, 2022), I utilised thematic maps at this stage to assist in the visualisation and organisation of themes and sub-themes, as illustrated in Figure 15 below.

Name	Files	References
Budgetary constraints – value for money	19	166
ITGovernance	11	61
Product Costing	14	43
Supply Chain	14	39
Value Creation	10	23
Controls existence and effectiveness	19	302
ITGovernance	11	61
KPI	17	47
LOC-Belief	11	19
LOC-Boundary	15	28
LOC-Diagnostic	12	33
LOC-Interactive	10	26
Product Quality	6	21
RM	9	34
Innovation	9	33
Process efficiency	18	284
T2 - Innovation	19	1293
T3 - Product Costing	19	1013
T4 - Quality Assurance	19	764
T5 - Performance Measurement & Management	19	729
T6 - Definition of Big Data Analytics	18	329
T7 - Challenges	19	499

TM 181 Items

Figure 15: Searching for themes - Developing themes (Source: NVivo extract)

5.5.2.5 Phase 5: Refining and naming themes (Developing themes)

This phase required integrating themes from earlier phases to ensure that the themes and topic names accurately, completely, and succinctly reflected what was significant about the data with respect to the primary research question. This procedure entailed reviewing the data in greater depth to consider aspects beyond the subject, utilising comparisons with literature and linkages within and across themes. I formed themes through systematic analytical engagement with the dataset and everything I brought to it about personal positioning and metatheoretical viewpoints; I did not "emerge" in the data when I "discovered" them. (Braun and Clarke, 2022a). During this phase, my significant IT expertise and experience as an accountant helped to ensure that the themes generated from the dataset were relevant to using BDA to enable MCS. As the goal of this phase is to provide evidence-based findings to support report creation, each conclusion had to be supported by the data. The long process of finalising themes involved developing ideas for an "overall story" that addressed the main research topic. As a result, I created an evidence-based framework to answer the main research question in the concluding analysis section. Figure 16 captures the overarching themes guiding the discussion in the next section.

Phase 3-Developing Themes			
	Name	Files	References
	 T1 - Sustainability	19	773
	 T2 - Innovation	19	1293
	 T3 - Product Costing	19	1013
	 T4 - Quality Assurance	19	764
	 T5 - Performance Measurement & Management	19	729
	 T6 - Definition of Big Data Analytics	18	329
	 T7 - Challenges	19	499

Figure 16: Refining and naming themes - Developing themes [Source: NVivo extract]

5.5.2.6 Phase 6: Creating the report

In this phase, I developed a comprehensive analytical narrative with concluding themes that address the primary research question. This final stage of the analysis provides sufficient evidence of the themes extracted from the data. It demonstrates how these themes interact with one another and with the literature to address the research question(s). From this perspective, phase six represents the completion and final review of the report, which I started composing before starting my thematic analysis (Byrne, 2022).

To grasp the complexities of how BDA support MCS in the agri-food and beverage industry, it is first necessary to reconstruct the sequence of events as they unfolded. The narrative that follows, drawn primarily from interview data, provides the contextual foundation for the subsequent interpretive analysis. This section offers a structured account of the case, organising the raw empirical material into a coherent chronology. Its purpose is not to analyse but to equip the reader with a clear and comprehensive understanding of the empirical landscape of the cases.

5.6 Chapter Summary

Given the precise formulation of the research question and objectives, this study cannot be a straight cause-and-effect relationship, as the use of BDA to enhance MCS would be influenced by a variety of factors, including people, strategies, and software/hardware. The factors that affect the application of BDA to enhance MCS can be understood primarily through an interpretivist framework. This analytical method is facilitated by SST, offering a robust framework for examining qualitative data to understand the complex interactions between external and internalised systems in the agri-food and beverage industry. To navigate the intricacies and uncover the nuances of using BDA to facilitate MCS, an abductive approach was adopted, through which findings were generated via qualitative data collection and analysis methods, including interviews and document reviews. Given the exploratory nature of this study, semi-structured interviews with industry experts were conducted as part of a multiple-case study. Thematic analysis was the most suitable approach for this study because it not only describes the data but also interprets and organises participants' accounts into coherent patterns. By systematically identifying recurring ideas, behaviours, and meanings, it produces clearly defined themes and concepts that directly answer the research questions. These themes then become the organising framework for the findings chapter: each major theme generated during analysis is translated into a findings section, illustrated with selected quotes and examples. In this way, the interpretive work done in thematic analysis naturally shapes how the results are presented, ensuring a smooth transition from raw data to coded patterns, to structured findings and, finally, to the discussion of their theoretical and practical implications.

Chapter 6 Findings

6.1 Introduction

As discussed in Chapter Five, adopting an abductive approach was deemed to be the most appropriate way to understand the complex relationship between BDA and MCS. This approach is most suitable for this study since it seeks to answer why, when, and how management uses BDA to facilitate MCS. The following analysis considers the complex relationship between the power of BDA and the personnel involved in the process. Chapter Five elaborated on the relevance of SST in accounting research and the rationale for this theory as an analytical framework for studying the BDA-MCS relationship. The key advantage of using this analytical framework revolves around the quadripartite cycle of structuration, which explains how the agent (agency) utilises their context (external structures) and conduct (internal structures) to determine outcomes when applying BDA to facilitate MCS (Figure 17).

The conceptual framework for this study posits that data generated from the factory floor are analysed to establish the connecting tissues linking the outcomes (expected or otherwise). At the same time, data analytics techniques are used to extract the relevant information needed to make informed decisions, given the sheer volume of data generated. These decisions are made by agents (humans) who depend on external structures (such as technological advances).

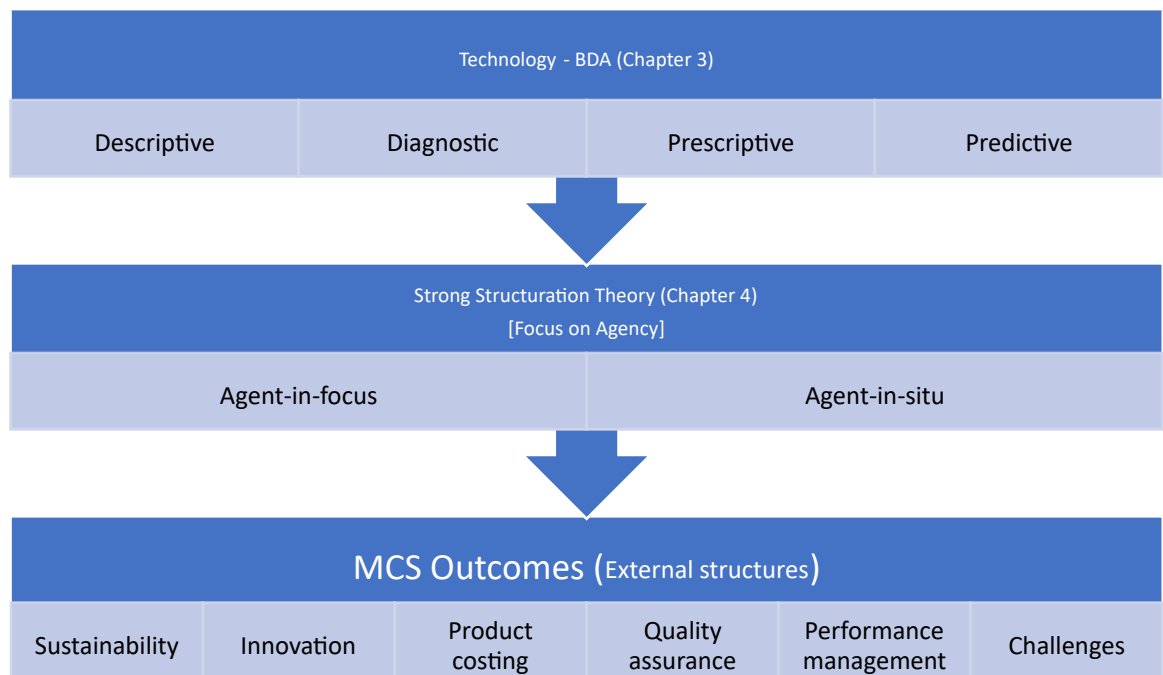


Figure 17: Interplay between BDA, agency and outcomes (Source: Author)

The use and development of BDA tools may be more dependent on the technical team, but the decision-maker must be familiar with the type of information required to make informed decisions. Hence, the agent's role is crucial in making optimal decisions to achieve the expected outcomes, placing SST at the centre of this study. Therefore, a recap of SST, especially the bracketing of its constituent components in the context of this study, is necessary before delving into the analysis. After a brief recap of SST, the bulk of this chapter presents the findings articulated as outcomes of the study, compiled through thematic analysis of data collected during the study (Section 4.5). To maintain participants' anonymity, quotes are referenced using "C" for the participating company and "P" for the participant. For example, C1P1 refers to the first participant from the first company, while "C1" refers to quotes from the first company's policy documents (as explained in section 5.4.3).

6.2 Outcomes as a result of structures

SST is used to investigate the application of BDA in MCS, providing a comprehensive framework for understanding the complex and dynamic interactions among technology, human agency, and organisational structures. This method emphasises the dual role of structures, the active role of human agency, the significance of routines and practices, the dynamics of power and knowledge, unexpected effects, and interactions with existing structures (Lee and Manochin, 2021; Lee *et al.*, 2023). This approach provides valuable insights into how data analytics can be shaped by the organisational context, thereby improving understanding of its impact on MCS. The investigation into using BDA to facilitate MCS as a social phenomenon reveals a complex relationship with those responsible for implementing BDA. In addition, it reveals how MCS design influences the use of BDA. Using SST as a theoretical lens, the findings demonstrate how various roles within the company's management influence the use of BDA to facilitate MCS, an outcome of structuration that depends on the interaction between management and their conditions of action.

While external structures provide an agent with their conditions of action, internal structures are the aspects of an agent that influence its behaviour. Interpreting these external and internal structures provides context for individual behaviour, particularly the interplay between them in BDA's role in supporting MCS. It is evident from the

findings presented in this chapter that the subjective nature of the managers, as individuals, is as influential as the objective characteristics of the structures with which they interact in using BDA to facilitate MCS. For some of the participating case study companies, this subjective element is minimised by involving different personnel at various levels of responsibility within the organisation. Individuals whose roles require deeper involvement in the MCS are consequently expected to possess a higher degree of proficiency in utilising BDA to enhance the functioning of that MCS within the organisation. This approach enables the analysis to progress along the sliding ontological scale (Stones, 2005), leveraging the ideas from the three major agents (roles) who matter in the use of BDA to facilitate MCS. Chapter Five explains that the financial controller, management accountant, and IT managers are the key agents (agent-in-focus or agent-in-situ, depending on their responsibilities) in this case study. The analysis in the next section (6.3) examines how these roles contribute to the use of BDA to facilitate MCS. Each role is matched to its contribution to various strategies that benefit from using BDA to facilitate MCS.

BDA is an enabling and constraining factor in executing these key areas of MCS. BDA techniques require skilful people to execute them and may therefore not be fully exploited due to a lack of these skills. Stones (2005) describes such limitations as external structures that may prevent the active agent from maximising the use of BDA techniques. The agents in this study (as explained in Chapter Five) have been identified as the financial controller, the management accountant and possibly the IT manager. Stones (2005) distinguishes agent-in-focus and agent-in-situ based on the agent's disposition to influence the structures and not just accept or implement what the structures provide. The term agent-in-focus refers to analysing the agent as an active agent within the structure. In contrast, agent-in-situ refers to analysing the agent as a product of the structure. The following analysis draws on the Financial Controller's involvement in decision-making regarding IT investments to collect and analyse data. At the same time, the management accountant utilises resources to collect and analyse data from the production floors, while being cognizant of the financial controller's decisions and the MCS's broader structure. The analysis considers both types of agents as they have different perspectives on how BDA facilitates MCS.

This consideration is evident in the analysis, which shows the extent of interconnections between the SST components and the MCS themes developed in this study. The data is generated from querying NVivo based on the number of codes matching SST and MCS themes (Appendix F – SST intersection with MCS themes. Although this is not a quantitative study, this extract highlights how SST components contribute to MCS's success. For example, innovation relies more on the general dispositions that equip the agent to think freely (individual or group experience) than on the impact of contextually specific knowledge (knowledge or resources provided by the organisation). In discussing the outcomes, I recognised the agency's influence in arriving at a particular outcome. The following section presents findings based on emerging themes from the analysis of data collected during the study.

6.3 Themes

From the analysis, six significant themes emerged as key constructs explaining how BDA facilitates MCS. These themes are (1) Sustainability, (2) Innovation, (3) Product costing, (4) Quality assurance, (5) Performance measurement and management, and (6) Challenges. Figure 18 illustrates these key themes as developed through the analysis in this study.

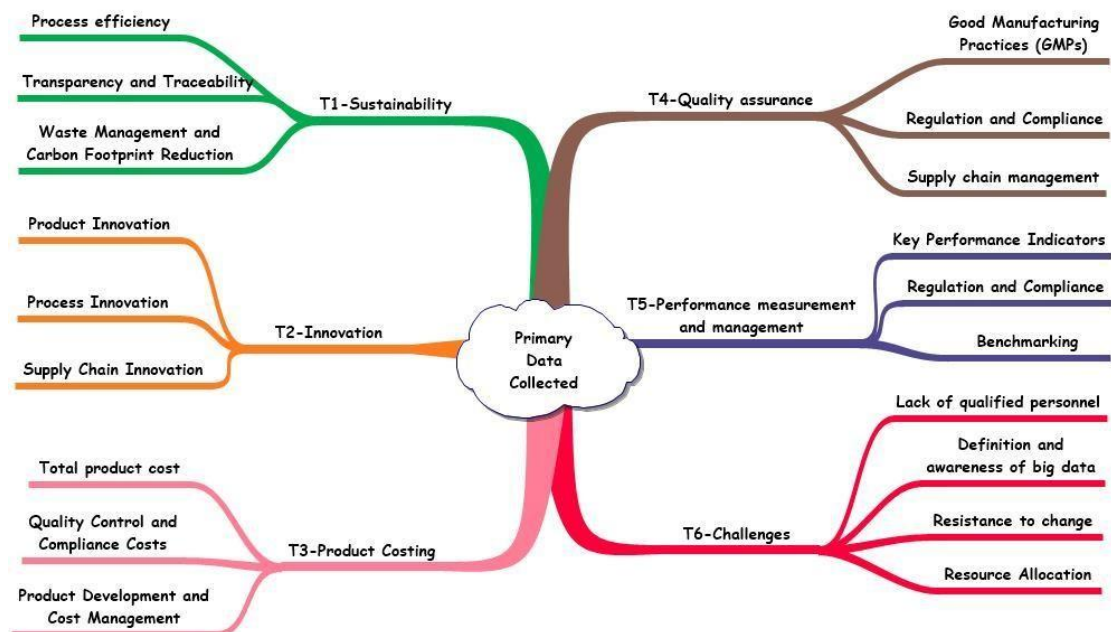


Figure 18: Emerging Themes

During the interviews, participants were asked questions to elicit their strategies. For example, they were asked: “As a manufacturing company, what are some of the KPIs

that drive your strategies?” A follow-up question sought to determine how data was collected to ensure the successful implementation of these strategies. *“What data is collected to evaluate them?”*

These questions enabled participants to describe the company's overall strategies and the types of data collected to ensure its success. The answers generate words and expressions that point to key strategies, such as sustainability targets. These strategies include efficient resource utilisation, effective waste management, optimised supply chain management, innovative product development, social responsibility and corporate governance, regulatory compliance, consumer engagement, and carbon footprint reduction. These strategies can be successfully implemented with the help of technology and innovation (Chen, Chiang and Storey, 2012). However, the extent of success is determined by the enablers and constraints defined by the company's rules, norms, and resources. These enablers and constraints are referred to in SST as the external structures (Section 4.2). In line with Perdana et al. (2022), the availability of BDA technologies can be an enabler and constraint to achieving the goals of these strategies. BDA involves gathering and analysing data to gain insights, but its success depends on the abilities of the humans charged with its implementation (agents). Therefore, to explain how BDA is currently used to facilitate MCS within the agrifood and beverage industry, it is necessary to understand the relevant structures and agents that interact to produce the desired results. The management accountant at a meat processing plant emphasises the importance of analysing the data collected to extract useful information for decision-making.

“The theory of gathering all the information is good, but the capability to turn that information into value is the biggest gap in everything” (CIP2)

This limitation stems from multiple factors, including the availability of the right technology to extract and analyse the data, the technical ability of the people involved in its implementation, the willingness of management to engage with the technology, and organisational policies and procedures. A more detailed account of the themes generated by this study (Figure 18) is presented in the following section, which examines each theme to elucidate how BDA affects the functions that comprise it.

6.3.1 Sustainability (T1)

In 1987, the United Nations Brundtland Commission defined sustainability as “meeting the needs of the present without compromising the ability of future generations to meet their own needs.” (UNAI, 1987). This definition, based on environmental goals, stated that sustainable development requires an integrated approach that considers environmental concerns and economic development. Sustainability is not independent of human conceptual frameworks; instead, it is always set in the context of decisions about the type of system to be sustained and the spatiotemporal scale (Allen and Hoekstra, 1992). In the agri-food and beverage industry, sustainability measurements are among the most important KPIs because the stakeholders interested in sustainability reporting are numerous (Maughan, 2022; Poppe, Vrolijk and Bosloper, 2023). For example, the government aims to ensure that companies operating within its jurisdiction adhere to sustainability targets, such as waste reduction (DAFM, 2021; Fox *et al.*, 2023; Hassoun *et al.*, 2024). Financial controllers and their teams must work diligently to meet these targets, as is evident in the majority of participants' vision and mission statements and as revealed in interviews. Understanding sustainability is one of the significant challenges in its implementation, especially due to the lack of consistent definitions of sustainability in the literature (Moore *et al.*, 2017). Powell and Romero (2022) see the potential for achieving sustainability as a balancing act between the triple bottom line and digital and smart manufacturing technologies.

Sustainability goals differ across industries, with no “one size fits all” approach, and they are often associated with other organisational goals or strategies. For example, sustainability assessment is an important approach for decision support in waste management systems, but both “ecodesign” and “quality and sustainability value” could be regarded as embraced within “innovation” (Souza *et al.*, 2015). Environmental aspects of supply chain management deserve greater focus, since sustainability and economic growth can be pursued together rather than being fundamentally opposed (Vachon and Klassen, 2006; Benton *et al.*, 2021; Maughan and O’Dochartaigh, 2023; Rockström *et al.*, 2025). This change in viewpoint indicates that organisations ought to view environmental issues as opportunities to bolster their

competitiveness, boost their reputation, and contribute to a more sustainable future, rather than as impediments to economic progress.

Although there may be a temptation to skip some steps toward achieving sustainability targets (to save costs), companies are likely to resist this temptation, as doing so may save money but could put them on the wrong side with regulatory bodies or the public (other stakeholders). In this context, they are likely to seek more accurate information to inform their decisions.

“I suppose, other areas, in terms of legislation or regulation, will be, you know, the kind of quality information that we need to retain on grading product quality results, you know, so that we can trace any potential issue that might happen with the use of a product” (C4P1)

“If one doesn’t understand what they’re doing or why they’re gathering the information, they may present an incorrect matter” (C1P2)

“We need to get the correct information at the end of the day” (C2P1)

In the agri-food and beverage industry, sustainability is achieved through the implementation of various strategies that ultimately help the company become sustainable. Sustainability in an agri-food and beverage company involves adopting practices that minimise environmental impact, promote social responsibility, and ensure economic viability while producing quality food products (Smith, 2011; Pagell and Shevchenko, 2014; Paulraj, Chen and Blome, 2017; Maughan and O’Dochartaigh, 2023, 2025). This approach helps conserve natural resources and meets consumer demands for ethically produced goods. The agri-food and beverage industry operates in a dynamic environment where internal operations and external factors continually interact and shape one another. These crucial objectives reflect the three most important strategies for an agri-food and beverage company’s survival in a highly competitive business landscape.

1. The efficient use of resources (Rikhardsson and Dull, 2016; Awan *et al.*, 2021; Konur *et al.*, 2021)
2. Waste management and reduction of carbon footprint (Awan *et al.*, 2021; Konur *et al.*, 2021)
3. Meeting regulatory and consumer needs through transparency and traceability (İndap and Tanyaş, 2023; Essien *et al.*, 2024)

A review of documents from the participating companies reveals a predominant interest in sustainable goals.

“Our emissions reduction targets are approved by the Science Based Targets initiative, demonstrating our commitment to building a sustainable future and limiting global warming to 1.5°C.” (C1)

“We are committed to exploring new avenues of innovation and actively engaging with our stakeholders to shape a sustainable future for XX.” (C12)

“All Our Futures is in line with C1’s vision as a family-owned group of companies to provide a safe and nurturing environment for their staff and colleagues, to be active and positive contributors in the communities in which they live and work and to be good stewards of the environment” (C1).

“For 200 years, we have been driven to produce at the highest standards while keeping the environment in mind. We embarked on a journey to teach our methods and reduce our carbon footprint on the environment” (C2).

A recurrent theme in the interviews was a sense amongst interviewees that sustainability relies on multiple strategies in the agri-food and beverage industry due to various societal pressures from consumers and regulatory bodies.

“If you can develop strong customer relationships and partner with customers to create tailored products for their recipes, you can charge more for that, and you get more value for that, right? So we’re always trying to see how we can uplift the value of our products by doing something slightly different for our customers” (C4P1) “I

suppose, at the back of all of that, we have traceability, not just of the products themselves in terms of your raw materials back to the supplier or finished products to customers” (C5P1).

“I suppose, other areas, in terms of legislation or regulatory, will be, you know, the kind of quality information that we need to retain on grading product quality results, you know, so that we can trace any potential issue that might happen with use of a product” (C4P1)

For example, effective controls may stifle innovation and, consequently, sustainability (Ashford and Hall, 2011; Johnstone, 2021; Ji *et al.*, 2025). At the same time, sustainability is a product of effective controls on resource distribution.

“We don’t have infinite resources to tackle all these problems. So we need to make sure we tackle the stuff that we can” (C1P3)

Data from interviews also reveal a commitment to attaining targets required for the companies to be sustainable. Sustainability and supporting sub-themes (Appendix G – NVivo extracts) list sub-themes that support agri-food and beverage companies in attaining their sustainability goals.

Generally, organisational policies and sustainability procedures determine the success in pursuing sustainability goals. These policies and non-organisational requirements form the basis for action towards attaining sustainable goals for the company. BDA tools can facilitate the collection of the required information to support an organisation’s sustainability objectives. For example, regular review of customer feedback in the agri-food and beverage industry can help the company shift towards more sustainable sourcing of raw materials to better satisfy customers.

“So, it’s all those experiences, and we’re trying to bring them all into one place to capture all of our dealings with every single customer within the business, whether a consumer or retailer” (C2P1)

Personnel at various levels of the organisation may have to rely on their understanding of these policies, which is usually based on their experience and responsibilities. Management uses prescriptive analytics to establish organisational sustainability goals, based on information from descriptive and diagnostic analytics. Understanding how data is generated and used depends on distinguishing between human and nonhuman actors.

Efficient use of resources:

One of the key issues in the manufacturing industry is reducing energy consumption and conserving natural resources, such as water. Most agri-food and beverage companies aim to reduce energy consumption through efficient manufacturing processes, the adoption of renewable energy sources (such as solar, wind, or biomass), and improvements to facility insulation and equipment performance. Advances in technology are the principal facilitators of this evolving strategy. Today's factories are considered smart ecosystems with humans, machines and devices interacting for efficient manufacturing of products (Konur *et al.*, 2021). The financial controller of a chocolate manufacturing company stated:

“We are trying to make sure that we’re tapping into an IT platform that will bring benefits and efficiency to our business (C3P1)”.

IT platforms are increasingly being considered one of the primary resources (supported by data analytics) that agri-food and beverage companies are investing in or planning to invest in to improve their manufacturing processes. The IT manager of a crisp manufacturing company stated:

“When we collect this data, we’re able to look at it and analyse it and see, which obviously, different data relates to machine efficiency, and then directly sometimes relates to product quality” (C2P3).

By taking steps towards efficient resource usage (situational knowledge), the IT manager builds on their knowledge and experience as an IT professional (general

disposition) to ensure the system generates the required data to fulfil the company's strategies.

“The key areas are operations and security, which are basically keeping the lights on and making sure that all our systems and applications and the technology that we need to use to run our business are up and running, safe, and protected, are kept patched and kept secure” (C12P2).

Although everyone is responsible for their area within the whole organisation, the IT manager must be familiar with the manufacturing process to provide adequate systems support to those on the production floors.

“So, each person within each area has responsibility for their element of delivering the core values, the guy in the production line knows what he needs to do to make sure he is delivering his element of the core values” (C3P1)

“IT is responsible for all the critical applications we use to run the business” (C12P2)

In some cases, the roles of financial controller, management accountant and IT manager are occupied by the same individual. In such cases, the requirement to be familiar with the manufacturing processes becomes less of a concern.

Most importantly, the IT systems must match the manufacturing processes to generate the required data to fulfil the company's strategies. The IT manager would possess sufficient localised industry knowledge to generate customised cybersecurity protocols for manufacturing-floor IoT devices or to deploy industry-specific resources (agent-in-situ).

“So then a roadmap to look at what additional information can be gathered from the factory floor to make data analytics easier and get more benefit from it” (C6P1).

Despite the drive to improve manufacturing processes, IT investment strategies focus on the value that can be created from each investment (Grover *et al.*, 2018; Côte-Real *et al.*, 2019). Constraints on the agent-in-situ may include mastery of niche knowledge

that is not transferable to other sectors within the same industry (e.g., an IT manager transitioning from a meat factory to a bakery). Similarly, transferring from a legacy software system can be challenging for the IT manager. The IT manager of a chocolate manufacturing company expresses this worry by stating:

“You know, there have to be certain controls around the technology that we’re purchasing to ensure one that it’s, you know, can integrate into our systems easily, that it’s, you know, best in class in terms of security and, and process design, etc, etc. and if we’re getting value for money” (C3P3).

In addition to energy conservation through efficient manufacturing processes, the other prime objective for agri-food and beverage companies is to maximise the use of raw materials to reduce waste and promote efficient use of inputs, such as optimising crop or livestock yields. The latter is covered in more detail under the product costing theme. Once the IT systems function as expected, the financial controller (or management accountant, in some cases) uses data analytics to monitor efficiencies, such as energy usage, across the manufacturing process. By analysing trends and anomalies, they can identify areas where energy is wasted and suggest improvements to reduce consumption.

Waste Management and Carbon Footprint Reductions in light of Seasonality As part of the procedure to ensure efficient use of resources, the financial control function uses data analytics to monitor waste generation and identify areas where waste can be reduced (external structure). This process includes tracking the effectiveness of recycling programs and other waste management strategies. The financial controller (agent-in-focus) of a pet agri-food and beverage company expresses his concerns about identifying wastage as follows:

“What wastage there is, what energy per ton of finished products, what labour cost per ton of finished product, what wastage per ton of finished product” (C10P1).

Implementing strategies to reduce food waste at every stage of production, from sourcing to processing, packaging, and distribution, is necessary. This approach may include repurposing by-products, utilising surplus products for secondary markets, or

converting waste into animal feed, compost, or bioenergy (Lee *et al.*, 2019; Ayilara *et al.*, 2020; Shurson, 2020; Vazquez Melendez, Bergey and Smith, 2024)

Seasonality is one of the common characteristics of the agri-food and beverage industry. Either the customers' demand is seasonal, or the supply of raw materials may be seasonal (external structures). Depending on the source, seasonality, and other reasons, inconsistent supplies may occur that may require storage capabilities (Shurson, 2020). In either case, maintaining a sound supply chain management system is crucial. Predicting future trends in consumer behaviour and seasonality with great accuracy is, therefore, of great necessity in the agri-food and beverage industry.

“If we see trends in terms of quality, how can we do something different at a firm level to improve the quality? (C4P1)”

The most common cost associated with seasonality and poor supply chain management systems is wastage.

“It kind of all trickles down the purchasing, purchasing then takes that plan, and they feed that into their procurement section. They know that a supplier needs 12 weeks to fulfil orders, and it takes four weeks to deliver them. So, therefore, if you need that raw material in June, I need to order that raw material in April, or you’re not going to have enough time” (C3P1)”

Agarwal *et al.* (2024) suggest that predicting consumers' wants can help reduce needless inventory costs. Maintaining a sound supply chain management system and implementing the correct economic order quantity (EOQ) will minimise wastage, thereby reducing the product's overall cost. Predictive analytics can significantly facilitate EOQ implementation by providing the correct information used in the EOQ parameters and their management. The Financial Controller of a chocolate manufacturer explains the importance of managing the supply chain to match seasonality challenges as follows:

“It’s very seasonal. We sell it at Easter and Valentine’s, say we might do a tiny little bit in June for teachers, then we have a massive amount of sales at Christmas. However, our plant can’t just produce chocolate for Christmas. We have to run a plant for a whole year. So what they do is remove the sales trends from the previous three or four years. They plug that into a production model, and then that will generate, if you want to save that amount of chocolate for Christmas, based on my plant capacity, you will have to start producing on this date to make sure all your stock is in place for the retailers to take it and sell it then in December” (C3P1)

In the same way that predictive and prescriptive analytics can facilitate the supply chain system in the agri-food and beverage industry, supply chain service providers are joining the race to capitalise on the growth in the BDA sphere and offer their clients better service. Thus, supply chain professionals are now investing in automated technologies and robotics to empower their teams toward a more intelligent, safer and more streamlined workflow (Agarwal, Malhotra and Swami, 2024). This combined effort would result in a more efficient supply chain and could help reduce overall wastage costs.

Transparency and Traceability

The utilisation of BDA is paramount in boosting the traceability of ingredients in food products, effectively satisfying the dual objectives of regulatory requirements and customer expectations for transparency (external structures). For example, integrating digital traceability with food products through digital identifiers enables the tracing of crucial information such as growth conditions, batch numbers and expiration dates (İndap and Tanyaş, 2023; Zhou, Lu and Kumar Mangla, 2024), and consumers are willing to pay a premium price for traceable food products (Vriezen, Plishka and Cranfield, 2023; Tran *et al.*, 2024). Attention to traceability was highlighted throughout the interviews and on company websites. One of the IT managers (agentin-focus) said:

“Journey through the factory and record different things about them, and you know, what batches of meat went into this product for traceability reasons? So if there’s or there were to be a product recall, we could look up the batch number” (C1P3).

A meat processing company stresses the importance of traceability as follows:

“We like to say that great ingredients make great food. That’s why we insist on robust traceability, segregation, product control, provenance and animal welfare from our suppliers” (C1).

Similarly, a potato crisp manufacturer declares on their website that:

“Due to their family heritage, hard work, and passion for quality, the people at X are committed to producing Ireland’s finest potatoes, crisps, and snacks. Quality is a regulatory requirement and a critical mission for X” (C2)

An IT service provider (agent-in-focus) who specialises in providing software services to agri-food and beverage companies points to the fact that their systems are built with traceability in mind:

“So, you can look at any transaction in our software programme and within, I would say, within seconds, you can identify where all the raw materials came from, you identify particular products, you can, within seconds, identify which customers have got that product, okay, so you can do a trace upstream and downstream” (C5P1)

Overall

The majority of interviewees shared that the most common way to achieve sustainability is to ensure that it is appropriately incorporated into the company's strategies. Meanwhile, it is not sufficient to write out strategies without also trying to put them into action.

“I am privileged to lead a dedicated team which fully embraces the importance of Sustainability and the Environmental, Social and Governance (ESG) agenda to every aspect of the XX business” (C12).

According to Maas et al. (2016), corporate sustainability requires integrative measurement and management of sustainability issues rather than isolated applications of different organisational tools. It is therefore necessary to simultaneously use various

types of data and to realise the available resources and how they could impact a company's sustainability (Hämäläinen and Inkinen, 2017). Participant C1P1 echoed this view by saying, *"We use various other data capture mechanisms to monitor our operations and activities"* and *"need the system and capability to analyse that data to tell us the optimal parameters to produce the optimal product"*. Meanwhile, participant C2P1 stated, *"So we would have data from all over the business and read into very bespoke reports"*. Data is indispensable, but its analysis to gain insight is crucial to attaining optimal sustainability. *"Sometimes getting that balance around the data analysis, especially on big data analysis, is worth investing in because you're not quite sure what you'll get out"* (C2P1). BDA provides the necessary tools to extract data to help organisations attain sustainability targets. For example, predictive analytics provide a means to implement preventive maintenance. Efficient machines result in lower energy consumption and reduced pollution, making them more sustainable.

"Now, we have preventive maintenance with meters on each machine to see, you know, if the temperature fluctuates up and down. There may be an issue coming down the road with a machine" (C6P1).

Findings from this study suggest that agri-food and beverage companies must implement controls to ensure their manufacturing processes are efficient enough to support their sustainability goals. The study also provides evidence that sustainability is a product of multiple organisational strategies that seek to satisfy customers and regulatory authorities (external structures). Crutzen et al. (2017) found that large company managers (the agent-in-focus) tend to follow either a formal or an informal approach to management control. They conclude that most managers believe that informal rather than formal controls are more likely to influence sustainability-relevant behaviour (agent-in-situ). One of the benefits of BDA is its ability to harness data from non-conventional sources, such as informal procedures (agent-in-situ). BDA can therefore facilitate the attainment of sustainability goals for a manufacturing company much more easily.

6.3.2 Innovation (T2)

Innovation within the agri-food and beverage industry encompasses many critical elements that synergistically contribute to enhancing operational procedures, effectively addressing evolving consumer needs, and adhering to regulatory requirements (external structures). The key innovative issues primarily focus on operational procedures, such as new product development and process improvement (Feeney and Pierce, 2018). In the agri-food and beverage industry, this focus involves developing products tailored to individuals' unique health requirements and preferences, utilising advancements in nutrition science and data analytics to deliver personalised meal experiences (Nychas *et al.*, 2021). In addition to customers' requirements for traceable, healthier food, regulatory requirements pressure food manufacturers to be innovative (external structures). BDA techniques can alleviate pressure on governments and consumers by improving labelling for traceability and allergies (agent-in-focus). The interview results indicate that BDA can influence innovative initiatives in agri-food and beverage companies in various ways, as captured in themes that impact innovation in the agri-food and beverage industry. These themes and subthemes, which drive the specific strategies that lead to innovation, are listed in Appendix G – NVivo extracts.

Product Innovation

The most recurring research in this area has focused on new product development (NPD), the main driver of growth in the agri-food and beverage industry. Implementing a successful NPD strategy is widely recognised as a means for agri-food and beverage companies to attain a competitive advantage within the highly competitive business landscape (Santoro, Vrontis and Pastore, 2017; Feeney and Pierce, 2018).

“Working together, we believe that we can unlock value-added opportunities by combining our customer and market knowledge with our passion and knowledge for protein, process and culinary technology, new product development and creative innovation” (C1).

This advantage may include developing healthier options, such as alternative proteins (e.g., plant-based or lab-grown meat) and functional foods with added health benefits (Campbell and Henchion, 2014). Alternatively, competitive advantage can be achieved through reformulation (agent-in-focus), which may improve existing products (Hearn and Dalton, 2022). Reformulation includes altering recipes to reduce sugar, salt, and fat or incorporating healthier ingredients without compromising taste or quality.

“If you can develop strong customer relationships and partner with customers to create tailored products for their recipes, you can charge more for that, and you get more value for that, right? So we’re always trying to see how we can uplift the value of our products by doing something slightly different for our customers (C4P1)”.

Whether developing a new product or changing the mix of an existing one, there are always numerous implementation challenges. Making information available at a granular level can help overcome these challenges by providing details on raw materials, labour, and overheads that go into the product. Hence, Jagtap and Duong (2019) proposed that increased data availability and technical proficiencies have revolutionised creativity, competition, and productivity. They further suggest that organisations that effectively acquire big data and derive value from it have a significant competitive advantage over their counterparts, revolutionising their competitive strategies and operational practices.

“Sometimes, getting that balance around the data analysis, especially on big data analysis, is worth investing in because you’re not quite sure what you’ll get out” (C2P1).

It is widely believed that too many controls can stiffen innovation if implemented poorly. Innovation is a multifaceted and non-linear phenomenon involving multiple control methods across different stages (Feeney and Pierce, 2018).

Process Innovation

Data-driven innovation suggests that innovation processes could and should be automated, with technology and (big) data being at the core of the automation (Ylijoki

and Oy, 2019). Automating processes in contemporary manufacturing industries generates extensive, diverse data, facilitating a comprehensive perspective and fostering data-driven decision-making and agile innovation (Ylijoki and Oy, 2019). Therefore, the application of BDA in the agri-food and beverage industry has the potential to significantly stimulate innovation. This innovation is achieved by empowering enterprises to make well-informed decisions that enhance operational efficiency and develop new products that more effectively meet consumer demands. Effective optimisation of manufacturing processes depends on process complexity and the willingness of those implementing them. The success of such an endeavour depends heavily on obtaining the correct information.

“We need to get the correct information at the end of the day. So again, bringing people on that journey when we mapped out our processes” (C2P1).

Big data is helpful in real-time monitoring (using sensors) of the production process, identifying any anomalies or deviations from the standard that could affect product quality. Real-time data may be included in product manufacturing planning systems, such as SAP and other ERP systems, which can assist stakeholders in making more informed decisions regarding optimising resource use and reducing waste (Jagtap and Rahimifard, 2017). BDA can assist in implementing advanced technologies, such as robotics and automated systems, to enhance manufacturing processes. Improved manufacturing processes can enhance efficiency, reduce labour costs, and improve consistency in food production (Bronson and Knezevic, 2016; Konur *et al.*, 2021).

“Our line efficiency for product X is 95%. So that means there is only 5% downtime, which is quite tight; it’s fully automated, and that’s monitored (C3P2).

Automation plays a pivotal role by replacing manual processes with technology-driven solutions, speeding up production, improving accuracy, and lowering labour costs (external structures). Automation achieves this efficiency level by reducing the dependence on humans and the potential errors associated with human characteristics. Consequently, automation is expected to optimise food manufacturing processes and minimise downtime.

“So when something goes wrong, the more automated you are, the more you can survive, the more you can move forward, and you don’t have downtime” (C2P1).

Big data can strengthen and enhance the food processing industry through real-time data analysis and simulation, remote monitoring, and predictive analytics across the production process. Diagnostic analysis (agent-in-focus) can help agri-food and beverage companies identify inefficiencies and opportunities for improvement, thereby reducing costs and increasing productivity. A chocolate manufacturer highlights its eagerness to leverage data analytics to improve efficiency and production processes.

“We are trying to take this to the next level, to get the kind of efficiencies and productivity out of it” (C3P1).

Supply Chain Innovation

Supply chain innovation centres around traceability and transparency. Agri-food and beverage companies can implement technologies such as BDA to ensure transparency and traceability throughout their supply chains, thereby helping maintain food safety, quality, and ethical sourcing.

“So we look at what we buy, where we buy it from, what the stock turnaround is” (C10P1).

Logistics optimisation is also a key component of supply chain management and can be facilitated using BDA. Using data analytics and AI to optimise supply chain logistics ensures timely delivery, reduces costs, and minimises food waste (Vern *et al.*, 2024). BDA can more accurately predict demand patterns by analysing historical supplier data, seasonal trends, and market conditions, thus reducing waste, optimising inventory levels, and ensuring timely delivery.

“It kind of all trickles down, is your purchasing, purchasing then takes that plan, and they feed that into their procurement section. They know that a supplier needs twelve weeks, while for others, it takes four weeks to deliver. So, therefore, if you need that

raw material in June, I need to order that raw material in April or you are not going to have enough time” (C3P1)

“So we had two suppliers for one product, our main supplier was in the UK, and then we had sourced another supplier of the same raw material in Europe, slightly more expensive” (C3P1)

Meanwhile, by employing diagnostic analytics to analyse continuous data from various suppliers, food manufacturers can identify the most reliable and cost-effective suppliers, thereby improving quality and reducing costs. Predictive analytics also ensures that raw materials for manufacturing processes are available on time. Global positioning systems (GPS) are key to this function, as highlighted by the IT manager of a dairy processing company.

“So these trucks use GPS for tracking, and it’s collecting data as they move from farm to farm to farm to farm, to where snap and all that data about what farm they’re on, which farm to the gold for second, and that data feeds into a route planning system” (C12P2).

Visualisation is crucial for synthesising and displaying information to facilitate decision-making across all BDA applications.

“That, to me, is an example of big data that we need to have the capability to analyse and visualise in a way that is useful to make any decisions useful to understanding trends” (C4P1).

Innovation has always been the cornerstone of the success of the agri-food and beverage industry in gaining a competitive advantage (Feeney and Pierce, 2018). Companies in this industry often operate on tight budgets but must develop products that entice a diverse customer base. Coupled with the challenges posed by government regulations and consumer expectations, food manufacturers must innovate to survive. Product innovation has long been a prime KPI for most manufacturing companies. However, process and supply chain innovations can be equally important in agri-food

and beverage companies due to the complexity of manufacturing processes and the intricacies of the supply chain caused by traceability requirements.

“I suppose, at the back of all of that, we have traceability, not just of the products themselves but also in terms of your raw materials back to the supplier or finished products to customers” (C5P1).

Digital traceability and sustainability performance are driven by product and process innovation, both guided by supply chain innovation (Zhou, Lu and Kumar Mangla, 2024). Predictive analytics facilitates this mediating role of supply chain innovation by mapping and securing the most efficient supply chain system.

“We have built-in contract prices with a lot of our key suppliers, so there’s no risk, the price goes up, the price goes down doesn’t matter to us, we still were locked in at that price for a period of time, we might end up losing money, but at least we have that certainty to plan forward that we know our price” (C3P2)

6.3.3 Product Costing (T3)

Drury (2018: 26) defines product costs as “those costs that are identified with goods purchased or produced for resale. In manufacturing organisations, costs are attached to the product and included in the inventory valuation for finished goods or for partly completed goods (work in progress) until they are sold; they are then recorded as expenses and matched against sales for calculating profit”. Manufacturing cost is broken down into prime and conversion costs. Drury (2018) describes prime cost as consisting of all direct manufacturing costs (direct material and direct labour). In contrast, conversion cost represents the cost of converting raw materials into finished goods (the sum of direct labour and manufacturing overhead costs).

Prime cost can be assigned to the product (provided that the costs are accurately recorded when they are incurred). However, the conversion cost is typically more challenging to allocate because overhead components cannot be directly allocated to the product. This challenge makes the allocation process overall more problematic. Cost accounting is essential in every circumstance to arrive at an accurate cost estimate for products.

“The Holy Grail for any food company is to know, when they go into a meeting with Tesco, SuperValu, or whoever it is, you know, what’s my product costing?” (C5P1)

“So by having the Bill of Materials correct, you’re able to build accurate product cost” (C6P1)

In the agri-food and beverage industry, product costing is the process of estimating the overall cost incurred to produce a specific food product. This process can be challenging to record accurately. The precise understanding of these costs is necessary when setting prices, sustaining profitability, and effectively managing resources. *“How much do I need to get to give me, you know, X percentage margin, so that I know that, you know, at the end of the week, month to a year, that I’m actually going to be in profit, you know, knowing that I have a certain amount of fixed costs as well” (C5P1)*

Thus, product costing supports the operating manufacturing process, steers budgeting and investments, and, in addition, significantly supports strategic decisions to shape a future product portfolio (Walter and Leyh, 2017). Changes in manufacturing technology, global competition, information costs, and customers’ demands for greater product diversity have driven the need to improve the sophistication of product costing systems (Al-Omiri and Drury, 2007). With technological advances, product costing systems are becoming more sophisticated and rely on accurate information being fed into them. BDA can significantly contribute to optimising product costing in the agri-food and beverage industry by providing actionable information and insights that lead to cost reductions, efficiency improvements, and better decisionmaking. Product costing systems in the agri-food and beverage industry can be complex due to the intricacy of manufacturing processes and the wide range of raw materials used. The Financial Controller of a meat product manufacturer states this emphatically:

“There are 100 different products, with 100 different recipes and 100 different ingredients. All of these are monitored and measured to determine the optimum parameters to arrive at the most efficient and optimum product” (C1P1).

The importance of monitoring raw material inputs was echoed by the Management Accountant of the same company as follows:

“Because we obviously are buying a lot of raw materials, and the price of raw materials has just gone up and up and up and up and up. So the cost per kilo was never more important” (C1P2).

The results of a typical product costing system might affect other significant aspects of the agri-food and beverage industry. For instance, if the entire cost of a product is computed incorrectly, the selling price will also be inaccurate. As a result, the product may be sold at a price higher or lower than the amount typically charged. The implications of such poor accounting could significantly impact the company's ability to sustain a competitive edge in an increasingly competitive industry. External factors typically influence raw material costs. The price of raw materials is categorised as an external factor within the SST framework, as it can influence the final product's price regardless of the production process's efficiency. Management may implement organisational techniques (situational-specific knowledge) to mitigate the effects of raw material price fluctuations (external structure), drawing on their industry experience (general disposition); nonetheless, these measures may not prevent adverse effects on the end product's pricing (outcome).

It is also important to note that product costing methods affect the expenses related to product quality and compliance. This control component is critical in the food production business because if raw material and ingredient costs are not accurately tracked, management may make detrimental decisions that affect the company's overall success. For instance, if the accounting system is not functioning properly, management may be tempted to replace an expensive component with one deemed less expensive. This modification could affect the product's quality and component composition; nevertheless, this error might have been avoided if the product costing system had been functioning correctly. The Financial Control in a chocolate manufacturing company confirms the transformation that the analysis of data brought to their product costing system, as follows:

“Even though the data was there, it wasn't integrated, and we weren't able to use it ... we didn't know if we were overusing or underusing raw materials, or if labour was too high or too low” (C3P1)

Product development also benefits from a robust product costing system, which facilitates practical cost analysis. For example, Feeney and Pierce (2018) indicate that the accounting information reviewed during stage 4 (business analysis) of new product development is specific and detailed. It sets out financing options, vendor quotes, and expenditure estimates. The application of predictive analytics can yield the desired results when faced with a future occurrence with some element of uncertainty. By utilising BDA in these areas, food manufacturers can improve their efficiency, identify opportunities for cost reduction, and ultimately achieve more competitive pricing and higher profitability through a better understanding of cost determinants. (Appendix G – NVivo extracts) summarises the sub-themes that affect how product-costing systems operate in the manufacturing industry.

Total product cost (Direct and OH costs)

Drury and Tayles (2005) define product cost as including all the expenses in bringing the product to its state of completion. These costs typically include materials, labour, and overhead in the agri-food and beverage industry. The challenge for companies is to define the accounting principles for raw materials, direct labour, and variable overheads, and to identify the most appropriate basis for allocating indirect overheads. Each cost component and its subcomponents are recorded throughout the production process, and the information must be extracted from the data to be useful to decisionmakers. Therefore, BDA techniques can be used to determine the total cost of a product in agri-food and beverage companies (Appelbaum *et al.*, 2017). Descriptive and diagnostic analytics can help organisations determine the precise cost of each unit by understanding and accurately tracking these costs. Accounting accurately for a product is critical for pricing, budgeting, and profitability analysis (Marotta, Krahnhof and Au, 2022). During the 1980s and 1990s, product costs were predominantly labourintensive, as they had been in the early stages of industrialisation. In modern manufacturing industries, labour costs are diminishing, giving way to dominant

overheads as technology-driven manufacturing becomes the norm. The fluctuation in material prices depends on various factors, including demand and supply, quality, geographic location, and supply chain efficiency.

“Because we obviously are buying a lot of raw materials, and the price of raw materials has just gone up and up and up and up and up. So, the cost per kilo was never more important” (C1P2).

“So it allows you to see through the live stock system of how many bags and boxes you physically have left in stock. So it helped us as well with ordering, and so that you don’t have too much stock or you have too little stock” (C6P1).

Raw materials must be available at the right moment to avoid stockout or overstocking, and wastage (Dadhaneeya, Nema and Arora, 2023). The cost of stockouts and overstocking can be enormous. For example, agri-food and beverage companies that run out of raw materials during a production run may need to pay a premium price to guarantee production.

“We will have scheduled adherence, which is how many of our deliveries from our external suppliers were delivered on time, so that we didn't lose production time due to missing materials” (C3P2)

These extra costs would affect the product's total cost and, consequently, the selling price, depending on the organisation's costing technique. Other costs may be incurred due to lost sales or customer attrition. Technologies like descriptive analytics can facilitate the analysis of historical data on raw material prices from various suppliers, tracking fluctuations and trends (Vazquez Melendez, Bergey and Smith, 2024).

Predictive analytics can forecast demand for specific food products, enabling organisations to adjust raw material procurement and prevent overstocking or stockouts, thereby minimising storage and spoilage costs. Organisations face difficulties in inventory management due to erratic demand patterns. Some had surplus inventory for products with diminished demand, whereas others experienced stockouts for things in strong demand (Agarwal, Malhotra and Swami, 2024). The product cost

can be reduced by applying a realistic economic order quantity to minimise overstocking or stockouts. Combining descriptive, diagnostic, predictive and prescriptive analytics will make this possible.

In addition to managing raw materials inventory, waste management can also contribute to more accurate product costing. Waste management is critical for agrifood and beverage companies from both environmental and cost perspectives. Raw materials acquired but not used may go to waste, incurring disposal costs. The wastage may also be absorbed into the product cost rather than being written off if proper accounting rules are not applied.

“So that has a list of ingredients that go into that, making that batch of product, and at the end of every run, we record what we've actually used. So then we have an automatic variance of what we wasted” (C3P2).

In the agri-food and beverage industry, BDA can optimise portion sizes, minimise spoilage, and reduce raw material costs by monitoring ingredient usage patterns and pinpointing areas of waste.

The second aspect of accounting for the total cost of a product is the labour cost involved in making it. Labour costs can be direct or indirect. Drury (2018: 24) defines direct labour costs as “those labour costs that can be specifically and exclusively identified with a specific cost object. In contrast, indirect costs cannot be identified specifically and exclusively with a given cost object”. In certain situations, distinguishing between direct and indirect costs can be challenging; consequently, accounting for them can be complex. However, there are well-established accounting principles to assign indirect costs to products. These methods rely on accurate data to be applied effectively. For example, a practical implementation of activity-based costing (ABC) depends on accurately identifying and measuring the activities that drive up costs. Utilising BDA, managers can obtain real-time data on diverse cost drivers, enabling them to identify the most appropriate option with the highest correlation (Amani and Fadlalla, 2017). Adriyendi et al. (2022) argue that descriptive and predictive analytics can be used in optimising motorcycle routes in road traffic by employing (data summarisation, visualisation, and dimensionality reduction) from

descriptive analytics and (feature selection, feature extraction, and grouping) from predictive analytics. Similarly, descriptive and predictive analytics can be combined to identify ABC's most effective cost drivers.

In addition to the issues discussed above, manufacturing organisations face another challenge when considering indirect costs, which can be viewed as direct costs in certain circumstances. When determining product prices, for instance, the production supervisor's salary is considered an indirect cost. On the other hand, it is a component of the production cost, which ought to be assigned to the manufacturing department and then absorbed into the products by employing an appropriate absorption rate.

According to the study of production data, descriptive analytics can be utilised to determine an appropriate absorption rate for overhead expenses.

In conclusion, the production methods utilised in the agri-food and beverage industry can be rather complex, making it difficult to identify labour charges specifically and solely associated with a particular product. It is also possible for agri-food and beverage companies to have seasonal production, which means that sufficient planning must be done in advance to ensure that production is not affected. This dilemma constitutes an extra issue that ought to be taken into consideration. Wellknown factors (external structures), including market trends, real-time operations, cross-industry affiliation, delivery optimisation, customer orders, customised recommendations, and customer seasonal demands, drive seasonality in the agri-food and beverage (Isabelle *et al.*, 2020). This problem could be mitigated by having a reliable system in place to collect and analyse data from production operations. Predictive analytics can use descriptive and diagnostic analytics to forecast the labour required before the subsequent production plan.

Participants (agent-in-focus) acknowledged the existence of these difficulties and indicated that they employ various analytical strategies to avoid the impact of these challenges on their personnel expenses. For instance, a chocolate manufacturer uses analytical models to prepare for labour in various ways.

Forecasting labour demands based on seasonality:

“The other integral part of that is to have labour because our production facility is seasonal; we have to make sure we have our labour booked to come in, and the weeks that we require them, and so then again, they would run that back to an analytical model” (C3P1).

Forecasting labour demands to take advantage of current and future production plans (Dairy industry):

“Then you can forecast based on your current staffing levels, and the types of product you have in stock, you know, what kgs per hour an operator can get through so then, you know, if you’ve taught the people, you know what the plant is capable getting through in a week, so that, you know, you can then forecast forward, how much tonnage you need to keep them active working at an efficient level” (C6P1)

Contracting just the required labour demands:

“We take our labour in as we require it on a contract basis or through our own fixedterm contracts. If there's no production, we know a couple of months in advance. So we would make sure that we have no staff on site those weeks that we don't need them” (C3P1).

As mentioned above, in the modern manufacturing industry, overheads represent a greater proportion of product costs, and allocating these overheads to products presents a significant challenge for management accountants. Terzioglu (2012) noted that in the early 1920s, direct labour comprised most of the total cost of manufacturing, and allocating overheads using direct labour hours or direct labour cost was sufficient for inventory valuation purposes, which was the primary object of cost accounting. However, the upsurge in manufacturing overhead as a percentage of manufacturing cost at the expense of direct labour and the proliferation of product lines complicated the otherwise relatively straightforward process of overhead cost allocation (Terzioglu, 2012). This evolution in manufacturing processes has made accounting for overhead costs challenging, necessitating a costing system that aligns with the company's activities.

The ERP system (agent-in-focus) used by one of the participants is designed to facilitate data collection and analysis for agri-food and beverage companies.

“We have developed a system that goes right through from manufacturing, right through right through to our finance and sales analysis” (C2P1).

The software developer of that same system describes it as primarily designed to capture data at various stages of the manufacturing process, providing the company with sufficient data to support every possible analysis and aid decision-making.

“So, you can look at any transaction in [the system] and within, I would say, within seconds, you can identify where all the raw materials came from, you identify particular products, you can, within seconds, identify which customers have got that product, okay, so you can do a trace upstream and downstream” (C5P1).

The system is robust enough to support any analysis of the data.

“We provide the capability to collect all the data through interfaces, whether they’re weighing scales, putting in weight, whether they’re touchscreens, where somebody is selecting information over their mobile handhelds that have the [the system] mobile application running on them to scan your products when they move from one place to another; where you pick a batch of products go into production much is scanning, if you’re sending product out, customers are also scanning them out” (C5P1).

It is possible to identify each cost component discussed earlier by conducting a descriptive and diagnostic analysis of data collected from the factory floor and from other sources related to the manufacturing process.

“So all of our machines in the factory have been linked, and they are running through an IoT device that is basically storing data for us” (C2P3).

“So basically, we are pulling in constant metrics and data from fryers and from all baggers, pull it into this source, and basically separating it all into different reports on key metrics of the factory and how machines are performing, how efficiently they are performing, which directly relates to our product quality” (C2P3)

Quality Control and Compliance Costs

Companies in the agri-food and beverage industry must have quality control in place due to regulatory obligations and the needs of their customers (external stakeholders). By analysing supplier performance and quality consistency, agri-food and beverage companies can choose suppliers that provide the best balance of cost and quality (Sarkis and Dhavale, 2015). Delayed or lost production due to raw material stockouts can significantly increase overhead costs, but these costs can be minimised by employing various data analytics methods. For example, predictive analytics can help ensure that the right amount of inventory is always on hand.

“We will have scheduled adherence, which is how many of our deliveries from our external suppliers were delivered on time so that we didn't lose production time due to missing materials” (C3P2).

In the agri-food and beverage industry, product reworks, scrappages, or recalls can increase overhead costs, thereby raising the overall cost of finished goods. Through analysis of quality-control data, it is possible to determine the financial repercussions of quality concerns for these overhead costs. The results of such an analysis enable manufacturers to take precautionary measures to eliminate these costs. If these preventive measures are well implemented, agri-food and beverage companies would rarely need to take corrective action, as any deviations from the original intent would be discovered immediately.

Product Development and Cost Management

In this modern era, manufacturing organisations face complex challenges in product development as customers ask for innovative, individually tailored, high-quality products at reasonable prices (Srivastava and Sahlot, 2023). Customers' demands impose constraints on agri-food and beverage manufacturing systems and thus form part of the external structures within the SST framework. The Financial Controller of a dairy processing plant narrate how a BDA visualisation tool helps stratify customers to ensure they get the right products.

“We would have used Tableau to organise all the data that we have on milk volumes, that we're going to process, what volumes we're going to process into the different

products, what are the prices associated with different dosage products and then what are the contributions of each product, each material code within that product to which customers so that we have a full visibility of the entire year” (C4P1).

The objective of producing high-quality products at affordable prices can only be achieved through strategic cost management (SST’s general dispositions), which requires manufacturing companies to have the right information at the right time. Drury (2018: 591) defines strategic cost management as “consisting of those actions that managers take to reduce costs, some of which are prioritised based on information extracted from the accounting system”. He also suggests that other actions are undertaken without accounting information. “They involve process improvements, where an opportunity has been identified to perform a process more effectively and efficiently, and which have obvious cost reduction outcomes and also the potential to increase customer satisfaction” (Drury, 2018: 591). The CEO of the software company involved in the study indicates that manufacturers might recognise procedures as wasteful. Instead, the issue may arise from a lack of accurate information, leading to poor judgment. He states:

“People will be looking at processes and think that they are not as efficient as they should be or that they are not as profitable as they should be. Whereas it could be just that the information gathered is incorrect.” (C5P1)

Another factor contributing to the successful production of high-quality food products at affordable prices is the adoption of appropriate costing techniques. These techniques include life cycle cost management, target costing, kaizen costing, activity-based costing, benchmarking, business process reengineering, just-in-time systems, and quality cost management. Life cycle cost management is probably the most relevant for product development, as organisations can better estimate, monitor, and optimise costs throughout the product lifecycle by leveraging BDA. Prescriptive, predictive and cognitive analytics apply during the design phase, while descriptive and diagnostic analytics apply during the manufacturing phase (Figure 19).

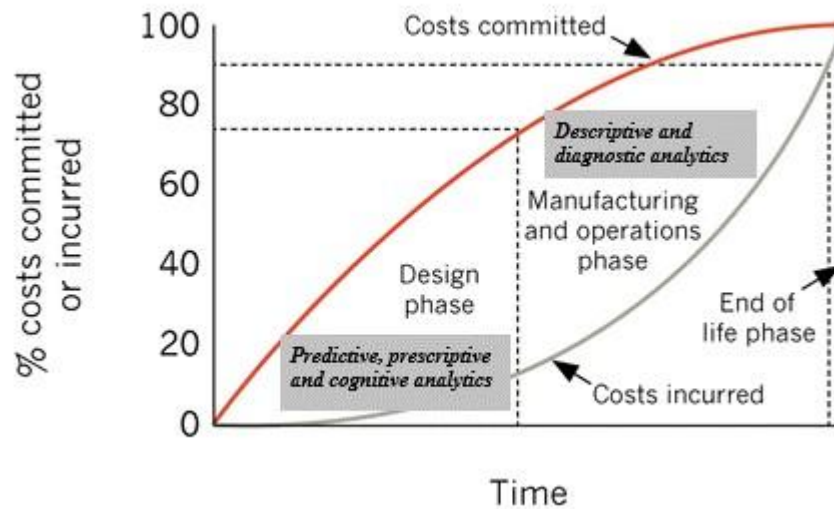


Figure 19: Product life cycle graph [Adapted from Drury 2018]

The outcomes of costing systems are significant to manufacturers, even though estimations can never accurately forecast actual future costs due to the unavailability of accurate data on time, ambiguity and uncertainty (Ibrahim, Elamer and Ezat, 2021). Optimising costs throughout product development involves estimating future costs (Walter and Leyh, 2017). As part of the production planning process, organisations would analyse whether production is feasible, make investment decisions for new production equipment, and begin directing resource allocations along procurement or production lines. Although around eighty per cent of product costs are committed at the design phase (Drury, 2018), even before production starts, most cost collection accounting only kicks into action during the actual manufacturing phase. The limitation is compounded by the lack of an accurate forecast of future costs due to the unavailability of timely and accurate data. Employing data analytics can help reduce ambiguity and uncertainty.

Applying predictive analytics to large amounts of data can assist managers in formulating the most suitable vision and plan based on evaluating future events (Ibrahim, Elamer and Ezat, 2021). Predictive analytics can utilise machine learning techniques to forecast future costs, such as warranty claims or disposal fees, thereby aiding more effective planning for long-term expenditures. Most importantly, for manufacturing processes, it is essential to forecast the correct amount of raw materials, labour, and overheads required to complete a product's production run without disruption.

“then you can forecast based on your current staffing levels, and the types of product you have in stock, you know, what kgs per hour an operator can get through so then, you know, if you’ve taught the people, you know what the plant is capable getting through in a week, so that, you know, you can then forecast forward, how much tonnage you need to keep them active working at an efficient level” (C6P1).

Standard simulation methods, such as "what-if" scenarios, can analyse complex projections, such as changes in material costs or production methods, to optimise resource allocation during production. BDA can greatly facilitate product lifecycle costing systems by integrating data-driven decision-making throughout a product's lifecycle (Ylijoki and Oy, 2019). This technology enables precise cost control, boosts operational efficiency, and supports strategic decision-making, enhancing product cost management (Alahmad, Neményi and Nyéki, 2023). Predictive analysis enables precise cost estimates for R&D, manufacturing, distribution, and end-of-life phases.

6.3.4 Quality assurance (T4)

Quality assurance in food and beverage products has never been more important, given the increased requirements from regulatory bodies as well as consumer demands (Charlebois *et al.*, 2024; Food Safety Authority of Ireland, 2024). Quality is one of the dominant external structures in this industry, as it imposes multiple constraints on internal structures to achieve organisational goals. The importance of quality assurance is articulated in the mission and vision statements of almost all participating companies. For example, the following declarations are found as part of their key strategies:

“We grow most of their potatoes and some of their seasoning, thus guaranteeing quality at inception”, and “Quality is a regulatory requirement and a critical mission for us” (C2).

“Food safety and quality policies are at the heart of the company's processes and procedures” (C3)

“We believe that only the best quality and distinct fresh taste is good enough for customers” (C4)

“We promise never to compromise on quality” (C7)

Quality is a demand from customers and regulatory authorities. The pressure is on the internal structures (including general dispositions and agents' situation-specific knowledge) to ensure that the quality of their products meets stringent standards. Throughout the production process, the primary components of product quality assurance in the agri-food and beverage industry are designed to ensure that food products comply with all applicable safety, quality, and regulatory standards. These components comprise a mixed set of preventative measures, monitoring and control processes, and continuous improvement practices.

BDA has the potential to improve product quality assurance in the agri-food and beverage industry by providing more in-depth insights, enhancing process efficiency, and facilitating proactive decision-making (Rikhardsson and Dull, 2016). The vast amounts of structured and unstructured data generated from sources such as manufacturing processes, supplier contracts, and market trends can be processed by BDA systems to produce information that supports quality assurance for the company's products. For example, supplier contracts can be used to confirm the traceability of raw materials that were used in manufacturing the food product. This information can be stored for an extended period and remain relevant should any dispute arise in the future. The ability to use data to back quality assurance has become more reliable with advances in technology like BDA, as a Financial Controller suggests:

“So that's the quality parameters within that milk for individual suppliers, the huge amount of data there that I suppose, if I go back 10 years ago, it existed in different systems. Still, no one was able to take the whole population kind of and analyse it. Today, you know, we do an awful lot of analysing around all of that information to try and understand how we influence it by protecting the quality, you know, if we see trends in terms of quality, how can we do something different at a firm level and improve the quality?” (C4P1)

The effectiveness of quality control measures in the agri-food and beverage industry depends on several factors. Fundamentally, the organisation's policy, intended to guarantee product quality, needs to be clearly expressed and strictly enforced. These policies are often guided by regulation and compliance requirements. These policies are then enshrined in the organisation's beliefs and boundaries, often captured in the mission and vision statements. Regular evaluation of the implementation of these policies ensures the system is operating as expected and the organisation's manufacturing processes are minimising risk. Hence, manufacturing companies invest heavily in technological systems to provide managers with a standardised platform. Such investment is also crucial for BDA technologies to ensure that sufficient data is available to confirm adherence to quality standards.

“Sometimes getting that balance around the data analysis, especially on big data analysis, is worth investing in because you’re not quite sure what you’ll get out”
(C2P1)

According to Ruivo, Oliveira and Neto's (2014) suggestions, organisations typically choose ERP systems to replace their present ones to achieve a more stable management accounting practice. This pattern was linked to the implementation of Standard Operating Procedures (SOPs), which, over time, increased efficiency and significantly improved the company's performance consistency. For specific products, such as ready-to-eat unpasteurised fermented plant-based products, the FSAI provides guidance on Good Manufacturing Practices (GMPs) for their production (FSAI, Note 37). Sowerwine (2017) suggests that one of these programs may be adequate to control specific hazards in a particular operation; however, other hazards may require the company to establish and monitor more specific preventive controls. They cited critical control points, which have long been regarded as the industry gold standard, as one such control.

Quality assurance relies on the proper application of well-known food safety management techniques such as standard operating procedures (SOPs), Good Manufacturing Practices (GMP), Hazard Analysis and Critical Control Points (HACCP), and supply chain management (SCM) (Singh, Shukla and Mishra, 2018). They further suggest that implementing appropriate safety checks, such as physical inspections, metal detection, and random product sampling, could help address this

issue. It is essential to take precautions to prevent food contamination at the beginning of the production process, when raw materials are sourced. Specifically, this is because food contamination can occur at any stage of the production process. In the case of the agri-food and beverage industry, supply chain management systems play a crucial role in ensuring product quality. (Appendix G – NVivo extracts) summarises various themes affecting quality assurance in the agri-food and beverage industry.

In the agri-food and beverage industry, SOPs and GMPs serve as key instruments for managers to stabilise production processes and ensure product quality. SOPs provide codified rules for how tasks should be carried out, particularly in settings with pooled interdependencies, thereby operationalising organisational norms through hierarchical oversight and process control. GMPs extend this focus to hygiene, equipment calibration, staff training and facility management, collectively reducing contamination risks and supporting product safety and customer satisfaction. From an SST perspective, SOPs and GMPs can be understood as external structures that embody organisational beliefs and boundary controls, shaping the conditions under which agents in plants and farms operate. These structures are activated in practice when agents draw on them to guide action. For example, when financial controllers and production staff monitor adherence to prescribed procedures and quality standards. For example, the financial controller of a meat processing plant stated: *Quality is never an accident; it is always the result of high intention, sincere effort, intelligent direction and skilful execution (C1).*

BDA strengthens this structuration process by providing accurate, timely information on whether these rules achieve their intended effects. Diagnostic analytics, visual dashboards, and IoT sensors monitor variables such as temperature and humidity, generating continuous data on process performance. When integrated within ERP systems, these technologies support real-time surveillance of deviations and enable prompt corrective action, turning formal procedures into effective control mechanisms. In SST terms, agents' ongoing use of BDA to monitor SOPs and GMPs illustrates how external structures are reproduced and occasionally modified through situated conduct, as practitioners interpret data, question existing routines and adjust practices.

Agri-food and beverage organisations operate under dense layers of national and international food safety regulations. These regulatory requirements, including obligations for record-keeping, traceability, and long-term data retention, constitute powerful external structures that both enable and constrain MCS. Companies must continuously interpret evolving rules, update internal procedures and demonstrate compliance during audits. SST highlights how these external structures only become consequential when internalised by organisational actors (such as quality managers or controllers) who possess the knowledgeability to translate abstract regulatory texts into concrete routines, training and monitoring practices.

“So we are going to use the data we never used before to look at efficiencies and problems and fix them” (C2P2).

BDA and machine learning enhance this translation by allowing companies to analyse large volumes of production and quality data to identify emerging risks, forecast potential non-conformances and evaluate the effectiveness of training and process changes. Continuous evaluation using BDA (such as tracking grading results or following up on deviations) supports diagnostic and interactive controls, enabling agents to question whether standards are being met and where additional interventions are required.

“So it is that constant evaluation of what you are doing. Knowing that maybe you need to be retraining continuously to make sure that, you know, standards do not slip and that people know what they are doing” (C2P1).

High-quality data archives, in turn, facilitate audits and reinforce traceability, thereby strengthening the recursive relationship between regulatory structures and organisational conduct that SST emphasises.

Effective supply chain management in the food industry is central to ensuring product safety, quality and cost efficiency across multiple organisational and geographic boundaries. Upstream supplier quality, logistics conditions and downstream distribution all shape the risk profile of finished products. Within an SST framework, supply chains can be conceptualised as networks of interlocking external structures (e.g., certification schemes such as BRCGS, contractual standards, shared data platforms) through which multiple agents coordinate activities. Organisational actors

draw on these structures to make sourcing decisions, design monitoring systems and negotiate expectations with suppliers.

BDA enables companies to mobilise these structures more effectively by integrating previously fragmented datasets (such as farm-level quality parameters, transport conditions, and manufacturing plant testing results) into comprehensive analytical views. This integration allows agents to detect trends, compare suppliers, identify early warning signals of contamination and support rapid traceability in the event of incidents. Certification frameworks like BRCGS institutionalise data-driven monitoring and risk assessment, reinforcing the expectation that organisations will continuously use analytics to evidence compliance and protect brand reputation. *“Besides quality, the BRCGS grading system is used throughout the whole supply chain to reflect the food hygiene practices of each food business operator. The BRCGS Standards thoroughly scrutinise every possible area where food safety could be compromised, and they are proud to be BRCGS AA rated”* (C8P1).

Through repeated use, these data-enabled practices contribute to the emergent structural outcomes highlighted by SST: more standardised quality expectations across the supply chain, stronger supplier relationships built on shared information, and a progressively more resilient and transparent food system.

Taken together, SOPs and GMPs, regulatory and compliance regimes, and supply chain management arrangements form a mutually reinforcing constellation of structures. When activated and mediated through BDA, they support robust MCS that enable agri-food and beverage companies to maintain safe, high-quality, and compliant production while continually refining their practices in response to new risks and opportunities.

6.3.5 Performance measurement and management (T5)

By providing insights that drive efficiency, quality, and innovation, BDA can significantly improve performance assessment and management in the food production industry (Dwivedi *et al.*, 2019). Improving operational efficiency is considered the cornerstone of every manufacturing organisation. This desire is even more crucial in the agri-food and beverage industry, which aims to achieve other

objectives, such as quality assurance, to satisfy customers and regulatory bodies. At the same time, food manufacturers must adhere to sustainability standards, be innovative and avoid waste. These goals are captured in the strategic statements of almost all the participating companies. For example, the following statements are extracted from their strategy statements (paraphrased for anonymity):

“Our approach indicates our dedication to delivering safe, healthy, and sustainable food products for clients worldwide while coexisting harmoniously with the environment.” (C12)

“We make investments in the recovery of waste heat and source ingredients in a sustainable manner.” (C1)

“Our distinctive framework guarantees that our products are centred on sustainable beef production and cattle farming practices.” (C7)

“Our sustainability objectives encompass a reduction of plastic waste by x% and a decrease in water use by x% through the introduction of rainwater harvesting.” (C8)

“Our company places a high priority on food innovation, and each of our facilities features a research and innovation centre that is among the best in the industry.” (C1)

Participants also affirm that their KPIs are developed in line with these aims. For example:

“Can we do it more effectively, efficiently and sustainably? Also, from an innovation point of view, it is what we’re delivering on a new product launch, and new products and new revenue streams that matter” (C2P1)

These and other objectives for measuring or assessing performance in the agri-food and beverage industry require accurate information. Data generated from manufacturing processes can be extracted and analysed using BDA, then transformed into the information needed for decision-making.

“We need the system and capability to analyse that data to tell you the optimal parameters to produce the optimal product” (C1P1)

Due to regulations and compliance requirements prescribed by regulatory bodies, agrifood and beverage companies have KPIs to meet these requirements and to generate profits for their shareholders. Some KPIs are also benchmarked against competitors and continuously monitored to ensure process improvements. Thus, the following section of this analysis focuses on these three main aspects: performance indicators, regulation and compliance, benchmarking and continuous improvement processes.

Key Performance Indicators (KPIs)

The advent of big data era is having a significant impact on the process industries, resulting in opportunities that have never been seen before for the achievement of smart manufacturing (Shang and You, 2019). Therefore, manufacturing organisations set goals to take advantage of these technological advances, but these goals must also follow the SMART acronym. The majority of these goals, as key performance indicators (KPIs) in the food production business, are designed around common activities that affect performance. KPIs enable organisations to concentrate on what is most important, make decisions based on accurate information, and change their plans to improve performance (Lapsley and Wright, 2004). In the agri-food and beverage industry, KPIs are typically based on enhancing operational efficiency, performing predictive maintenance, and managing inventories (Colledani *et al.*, 2014; Mourtzis, 2016; Omar, Minoufekar and Plapper, 2019). The evaluation of these KPIs relies on data captured from various sections of the organisation, which is then analysed to generate useful information for decision-makers. The Financial Controller of a meat processing plant points this out by saying:

“We use various other data capture mechanisms to monitor our operations and activities” (C1P1).

Agri-food and beverage companies can uncover bottlenecks, patterns of downtime, and inefficiencies by conducting an analysis of data from many production lines. This

analysis may include machine sensor data, throughput rates, and resource utilisation. For example, the management accountant in a potato crisp-producing company shares how they use data generated from the monitoring of their fryers to minimise issues before they occur as follows:

“At the moment, the IT guys are taking a lot of data from the actual machines and the factory, the fryers and all that and feeding it into cube reports with DIOMAC” (C2P2).

This approach has the potential to result in several outcomes, including streamlining procedures (Baduge et al., 2022), reducing waste, and optimising production schedules (Wang et al., 2023). It is essential for food manufacturers to optimise their processes because these processes affect other aspects of the products. As an illustration, process optimisation may affect product quality control, traceability, sustainability, equipment maintenance, compliance, and customer satisfaction.

Equipment downtime can be a costly experience for a manufacturing company, as lost sales cannot be recovered and may lead to lost customers. It can be argued that the holy grail in this industry is the ability to retain customers; thus, customer loss may exert pressure on management. In the SST framework, this constraint represents the external structures. In addition, scheduled employees may be paid even if they did not render any service during the downtime, further increasing the product's final cost (depending on the company's method of allocating overheads). The financial controller of a dairy processing company, considered the agent-in-focus within the SST framework, highlights the importance of preventive maintenance by stating that:

“Now, we have preventive maintenance with metres on each machine to see, you know, if the temperature fluctuates up and down. There may be an issue coming down the road with a machine” (C6P1).

Therefore, predictive maintenance is extremely important, and BDA can determine when it is likely that equipment may fail or when it will require maintenance (Colledani et al., 2014). The ability of machine learning algorithms to recognise

patterns that forecast breakdowns is enabled by historical data. Consequently, this enables businesses to perform maintenance before a repair or breakdown occurs.

Several measurements include production yield, downtime, and overall equipment effectiveness (OEE). These key performance indicators (KPIs) measure the efficiency of manufacturing processes, which transform raw materials into finished goods. BDA can be used to facilitate this KPI more efficiently, as the management accountant of a large dairy processing company points out in the following extract:

“We are looking at data under a heading that we call OEE, which is Operational Equipment Efficiency. So, we are trying to collect data about how effectively our production lines are running. So just from the factory floor, so you have things like, you know, the run times of machines, how long are they up along the down of the break, how quickly do they get fixed, we create we collected about run rates, we collect data, and part of that data is of the to the factory managers” (C12P2).

Data acquired by sensors on machinery and equipment, such as temperature, pressure, and vibration, can be analysed to gain insights into the machinery's performance and the equipment's health.

Inventory management is a critical factor in the agri-food and beverage industry, as in any manufacturing business. Although cost data related to raw materials, labour, overhead, and other expenses primarily concern the cost of a finished product, it also plays a crucial role in other aspects of the organisation's performance. For example, measurable KPIs could ensure the acquisition of high-quality raw materials at reasonable prices, resulting in favourable material usage and price variances. Data analysis can help continuously monitor inventory for quantity and other factors, such as obsolescence or perishability. The financial controller of a dairy processing company that buys milk from farmers in bulk recognises the importance of maintaining the right inventory quality at a price that saves the company money.

“[The ERP system] helps us have quite a detailed stock report, so you can see what volume of stock you have on hand and in terms of pricing as well” (C6P1). The above company utilises the ERP system to capture relevant data, which is then analysed and

yields various pieces of information, and the system integrates various functions, such as production, inventory, and finance, providing a comprehensive view of operations. Management accountants can use predictive analytics to forecast future organisational performance, which uses machine learning algorithms informed by descriptive analytics (Appelbaum, Kogan, Vasarhelyi et al., 2017).

Regulation and Compliance

Food safety regulations (external structures) are considered one of the most important cornerstones of the agri-food and beverage industry, prompting companies to set achievable targets to ensure compliance with the regulatory requirements. These goals may include regularly reviewing the company's performance in terms of adherence to compliance, hygiene, traceability, training, and customer safety. The management accountant of a dairy processing company alluded to the challenge of complying with restrictions on personal data as follows:

“So, you just have to put in a little bit more effort and work. There are legal constraints on what you can do with personal data. So you have to be aware of PPI (Protected Personal Information), your personal data, and your information” (C12P2)

Big data increasingly enables corporations to target optimal consumers by analysing personal information composites, facilitating predictions of future consumer behaviour (Roderick, 2014). Nonetheless, as people are increasingly willing to “give up” data for convenience or services and companies aggregate datasets, BDA outputs make it challenging to maintain control over personal information and preferences (M. Richardson, Petter and Carter, 2021). In addition to other challenges associated with manufacturing food products, this challenge poses a significant obstacle for food manufacturers. As a result, these businesses must assess their performance in this and other challenges from the manufacturing processes. Agri-food and beverage companies must evaluate their performance through their ability to maintain proper documentation, follow Good Manufacturing Practices (GMP), and ensure traceability (Rebezov *et al.*, 2024). The focus is usually on error metrics to minimise the impact on product quality. The expert informant who participated in this study emphasises the significance of capturing data in real-time to reduce errors in the manufacturing process.

“I think the big data analytics around machine data capture is very much about the now and making deep adjustments. Now, of course, you can also use that data to analyse trends in terms of the performance of machines.” (C5P1)

The IT manager is responsible for collecting and analysing data and is considered an agent-in-focus within the SST framework. The IT Manager of a potato crisp manufacturer highlights:

“So if we focus on error metrics, as such in those areas, we're mainly looking at machine performance and product quality” (C2P3).

This aspect of performance control is better executed through belief controls, as defined by Simons (1995). According to the belief-control theory, organisations must communicate their vision and mission to every employee so they are understood. These objectives are then evaluated for success through diagnostic control, which employs diagnostic techniques to explain deviations from expectations. Simons (1995: 34) defines a belief system as “the explicit set of organisational definitions that senior managers communicate formally and reinforce systematically to provide basic values, purpose, and direction for the organisation”. In the agri-food and beverage industry, all employees are expected to be fully aware of crucial regulatory requirements, such as Hazard Analysis and Critical Control Points (HACCP), and the entire production system to ensure food safety.

Diagnostic analytics are essential in identifying potential risks to production, supply chain, quality, and regulatory compliance. Management Accountants explore diagnostic analytics through internal structures, dispositions, and decision-making processes to maintain a stable supply chain system. This role is depicted as the agent-in-focus in the SST framework and aims to replicate or reproduce expected outcomes by drawing on internal structures. Developing and implementing strategies to mitigate recognised risks is paramount in the food production industry. Some examples of such strategies include preparing for unforeseen circumstances, diversifying suppliers, and implementing quality control procedures. BDA can help successfully implement these

strategies, thus resulting in optimal performance for the agri-food and beverage company. The management accountant of a chocolate production company explains how they hedge against the risk of fluctuating prices of raw materials as follows:

“we have built-in contract prices with a lot of our key suppliers, so there’s no risk, the price goes up, the price goes down doesn’t matter to us, we still were locked in at that price for a period of time, we might end up losing money, but at least we have that certainty to plan forward that we know our price” (C3P2)

One common performance metric is the frequency of violations detected during inspections or audits, for which companies in this industry strive to achieve zero noncompliance incidents. Other standard methods of evaluating performance in this industry include scores from internal or third-party audits for food safety compliance, maintained validity of certifications like HACCP or GMP, sanitation compliance rate, and frequency of product recalls due to safety concerns (Trienekens and Zuurbier, 2008; Charalambous *et al.*, 2015; Hu *et al.*, 2019). The most important measure is the fraction of employees trained on food safety protocols and regulations, and their subsequent assessment to maintain the standards (Prabhakar, 2008).

Benchmarking and Continuous Improvement Processes

The benchmarking process involves locating a "best practice" that can be found either internally or externally and then analysing how this can be utilised to enhance the organisation's present and future performance (Abdel-Kader and Luther, 2006). Benchmarking enables organisations to set realistic goals, facilitating continuous improvement in every aspect of their strategies. New ways of thinking and, in particular, accurate and reliable data are required for decision-making to improve organisational strategy continuously (Hämäläinen and Inkinen, 2019).

As highlighted in section 4.3.2.3, the regulatory framework constitutes the primary independent structure governing these organisations' financial operations, and food safety and traceability are mandatory standards that no company in this industry can disregard. This external pressure on the companies is depicted in the SST framework as external structures which require management to pay close attention. Due to the

specific challenges faced by the food production business, including regulatory requirements, government regulations, and customer demands, benchmarking and continuous improvement in manufacturing processes are crucial. The responsibility of management, as the agent-in-focus, to ensure that the processes always operate at their highest possible levels, is significant. By maintaining optimal operational levels, the company will also ensure excellent product quality, resulting in satisfied customers and, consequently, value creation for the business.

When it comes to facilitating benchmarking and continuous improvement processes in an organisation that manufactures food and diagnostic control systems, which utilise descriptive and diagnostic analytics, they play a crucial role. The formal frameworks these systems provide for performance monitoring and strategic advancement depend on quality information. The financial controller (agent-in-focus) of a potato crisp manufacturer emphasises the importance of quality information as follows:

“We need to get the correct information at the end of the day. So again, bringing people on that journey when we mapped out our processes” (C2P1).

Historical and present data can be obtained through descriptive and diagnostic analytics. This data can serve as a foundation for benchmarking, either internally or externally, depending on the specific situation. Manufacturing line efficiency, defect rates, and compliance audit scores are all examples of benchmarking that can be facilitated using BDA in this context. In terms of supporting continuous improvement processes, descriptive and diagnostic analytics can provide information that creates a feedback loop for ongoing improvements, offering insights that can be implemented. This approach is one way to support continuous improvement processes. Continuous monitoring of critical matrices, such as waste, customer complaints, and compliance failures, enables rapid identification of abnormalities and the implementation of corrective actions as needed. For instance, if HACCP sanitation scores were to decrease, this would immediately trigger an investigation and the implementation of corrective measures.

Through BDA, food manufacturers can enhance operational efficiency, make more informed decisions, ensure product quality and safety, and better meet customer demands. These objectives are crafted to mitigate the external pressures imposed on companies in this industry by the external structures. The agent-in-focus must draw on their internal structures, dispositions and situational-specific knowledge (Figure 9) to ensure these benefits are fulfilled. Consequently, this enhances efficiency, reduces costs, and provides a lasting competitive advantage in a highly dynamic industry.

6.3.6 Challenges (T6)

The complex operations of the agri-food and beverage industry, the rigorous regulatory environment, and the nature of the data generated and used in the industry create several obstacles when applying BDA in this industry. BDA technology is considered disruptive, which presents a challenge in itself. The introduction of new technology will impact organisational operations, and the SST framework categorises this effect as external structures that alter the organisation's *modus operandi*. External structures necessitate the involvement of the agent-in-focus to mitigate their effects and attain organisational objectives. Given its recency, it is unlikely that there are enough personnel available to harness the power of BDA.

Organisations that want to embrace this new technology may need to change operational procedures to take full advantage of what BDA offers. Generally, humans do not easily accept change unless we can see the reason behind it. Besides the challenge of embracing change, people might be ignorant of what they are venturing into and would resist taking the risk (agent-in-situ). The definition of what constitutes BDA was found to be another challenge to its successful application in the agri-food and beverage industry. Many participants defined big data primarily in terms of volume, overlooking the other aspects that characterise it. In addition to volume, big data is complex datasets generated at high velocity and require advanced storage, processing, and analysis technologies to extract meaningful insights (Hashem *et al.*, 2015; Gupta and George, 2016; Yaqoob *et al.*, 2016). Finally, the high costs associated with introducing new technology pose a significant challenge to implementing BDA in the agri-food and beverage industry. These challenges are now discussed separately in the subsections that follow.

Lack of qualified BDA personnel

The utilisation of many advanced technologies is sometimes linked to particular skill sets, which are frequently limited among the pool of workers capable of implementing them. As it typically takes some time for new technologies to spread throughout society, this problem is particularly prevalent in the context of new technologies.

“So, the pool of people who can actually use it is quite small. Even those who can use it probably don’t use it to its full potential” (C11P1).

Suppose businesses successfully enhance their employees' skills or recruit workers familiar with their existing technology. In that case, recent advancements in the same technology may have rendered their existing version obsolete. Consequently, the cycle of technologies is continually being upgraded, and the search for professionals with the necessary skills is becoming unending. Regarding the agri-food and beverage industry, there is evidence that BDA technologies are being utilised (Ayvaz and Alpay, 2021; Konur *et al.*, 2021). However, the deployment of this technology is considerably limited by a shortage of skilled workers, as with any new technology (Alemneh and Hastings, 2006; Jacobi *et al.*, 2014; Saltz and Grady, 2017). Because of this shortage of professionals (in data science, machine learning, and BDA), bottlenecks are created in the processing, analysing, and interpreting data (particularly those with expertise in agri-food and beverage). These bottlenecks, in turn, restrict the industry's capacity to utilise data-driven insights to enhance efficiency, quality, and innovation, as well as to comply with regulatory requirements. For example, when the management accountant of a potato crisp manufacturer was asked if they thought they were collecting and using as much data as is generated from the production floor, their response was:

“People aren’t trained, so we need to look at the people development, skills development to skill the people, and then the process to work properly” (C2P2).

The management accountant of a meat processing plant raised a similar point, in that:

“Anything that is quite chunky and quite big is very difficult to implement, and hence the word people gets mentioned several times. So, if you want to implement the work you do successfully, the installation stage is absolutely critical. The training you do is absolutely critical from that word I keep repeating, ‘people’.” (C1P2).

The simplest way to address these challenges would be to train both new and existing employees. Still, this option often presents other challenges since implementing BDA requires a cultural shift (Chow-White and Green, 2013). For example, training existing staff to adapt to new technology and work methods can meet with resistance. This resistance to change creates another level of challenge which needs to be appropriately managed.

Resistance to change and change management

The ability to properly manage change is essential to organisations' continued existence and growth; the more effectively an organisation can cope with change, the greater the likelihood it will prosper. Occasionally, change is mandated by external causes beyond the organisation's control, necessitating management's acceptance of the change to ensure survival in the industry. The SST framework asserts that the agent-in-focus (managers and their team) is responsible for mitigating or embracing the factors imposed by external structures (section 4.3.2.3). On the other hand, the organisational change process is a complicated endeavour; even the most minor error in change management could fail the change initiative (Song, 2009). Organisations often operate on principles well mapped out in their vision and mission statements, which form part of the basis for training newly recruited employees. Typically, once businesses have established their routines, they consider it financially impractical to undertake significant alterations to their operating processes (Appelbaum *et al.*, 2017). They become familiar with their responsibilities and boundaries, and may find it challenging to adapt to new ways of doing things. Hence, any change process must be managed carefully to achieve the desired results.

“It was quite difficult to manage the change, changing our processes, making sure we're taking extra steps to love what we're doing at all times” (C2P3).

Irrespective of the type of change being effected, people are always at the centre. Nonetheless, humans tend to be comfortable at certain proficiency levels and may hesitate to embrace changes from their current status quo. As highlighted by one of the participants, who stated:

“We are all creatures of habit. We all like to keep doing what we’re doing if we know how to do it in a very quick manner” (C1P2).

“If you asked us to change, as mentioned, we hate it; we have to be convinced. So that’s why I want to do it. The reason I mentioned that is that in order to implement this, which is what you’re trying to suggest, it means a change from the norm, and people don’t like that” (C1P2).

The management accountant of a meat processing plant also points out that employees must be comfortable with the change for it to be effective:

“Therefore, they do because it has to do something that they want to get used to; they’re relatively happy, but if you ask them to change and learn an entirely new way of inputting data, that can be extremely difficult unless it is formally shown in a proper manner that you’re comfortable with and understand” (C1P2).

Because food preparation often involves complex processes that require significant time to perfect, individuals may be reluctant to accept any adjustments to something they may have spent years learning. Employees who fall within the agent-in-focus in the SST framework frequently view introducing fresh ideas as a threat to the status quo they have established for themselves. For example, according to Baur et al.'s (2017) findings, the food safety culture challenges long-standing labour practices by incentivising workplace monitoring and discipline. They conclude that employees resist management’s message that food safety is important, and need to change their behaviour, complaining, “I’ve been doing it this way so long”. Similarly, employees of a manufacturing company could be resistant to implementing BDA-enabled procedures, even though BDA is advantageous to production processes. The IT manager of a potato crisp manufacturer pointed out how an organisation's move into big data analysis can trigger changes in the company’s processes:

“Based on your big data analysis, the outcome would be that there will be an outcome for changes to the company processes” (C3P3).

Meanwhile, the management accountant (agent-in-focus) of a meat processing plant emphasised the importance of considering the role of people in such changes:

“We can move on with these big to use your phrase big data analysis, and we’re going to put people to one side. They don’t matter anymore—wrong, wrong, wrong” (C1P2).

Therefore, it is essential to implement an effective change management process to ensure the successful adoption of BDA and achieve the level of innovation the organisation desires. In other words, employees must be encouraged to think freely and develop ideas. New ideas, seeds of innovations, often emerge subconsciously when our brain associates things with one another (Ylijoki and Oy, 2019).

“New ideas, or initiatives or marketing strategies come back, and everybody would be kind of working in unison to develop all these initiatives that would be assigned” (C3P2).

The financial controller of a dairy processing company articulates some of the challenges faced when introducing a new product used for visualisation:

“I know when I first approached the topic of, you know, building Tableau to give full visibility of our dairy ingredient sales, there was an awful lot of concern; what could that mean? How are we going to do it? How difficult would it be to use it? What value would you get out of it over and above the pivots we used to have?” (C4P1)

When managers or employees do not clearly understand what constitutes big data, this difficulty becomes much more acute.

Definition and awareness of big data

When the term "big data" is mentioned, the first and, in some cases, the only dimension that immediately comes to mind is size (Gandomi and Haider, 2015; Power *et al.*,

2018). In this study, most participants' definitions of big data aligned with this narrow view, as they focused primarily on the size or volume of the data captured or generated. For example, a management accountant at a crisp manufacturing company was unsure what big data could be. This uncertainty is summed up in their response to the question, "What constitutes big data?":

"Well, in my mind, data is data. OK, is big data the important data, or is big data the volume of data?" (C2P2).

You know, so you know it. It's how you look at it, I suppose, from my point of view, if I'm looking at an analysis of, say, FX accounts, and there are only 20 lines in it. Still, our sales have 10,000 lines, but the value in the FX can be big" (C2P2)

The financial controller of a dairy processing company echoed similar sentiments about the definition of big data, focusing on volume:

"Our demand volumes or demand prices, all the different capacities that are there in the different production plans, the volume that is coming in, against that balance, all that huge amount of data that we are working on every month. That, to me, is an example of big data that we need to have the capability to analyse and visualise in a way that is useful to make any decisions useful to understanding trends." (C4P1)

In response to the same question, "What constitutes big data?" the financial controller of a dairy processing company pushes the doubt to a different level (about other people, instead):

"The biggest one, I would say, and we're beginning to get there on this, the biggest one is, when someone starts talking about data analytics and big data and automation, people get very nervous, right, because they don't really know what that means" (C4P1)

"It was actually quite difficult at the start, for me speaking personally, because I was not familiar with the products with the mass data, but I was familiar with the process" (C3P2)

Sometimes, the participants thought of data and information as being the same.

“Instead of having a person collect all types of different information, but then what information you collect, you want to use it” (C6P1)

Generally speaking, the boundary between data and information, on the one hand, and between information and knowledge, on the other hand, continues to be ambiguous in ordinary conversation (Boisot and Canals, 2004). Such ambiguity has become less relevant as more data becomes available regarding volume, variety, speed, complexity, and so on. Hence, with the birth of big data, there is a clear distinction between data and information. The term "data" refers to unprocessed, undefined facts or figures devoid of context (Desai *et al.*, 2022; Grübel *et al.*, 2022). Data is not structured and has no meaning; it is the raw material used to generate information (Gullo, 2013; Krzanowski, 2023).

In contrast, information is structured and contextualised to offer meaning, which helps with decision-making and understanding. These differences are crucial for this study, as we seek to understand how data is transformed into information that supports decision-making in the agri-food and beverage industry. Proper analysis of data will generate helpful information. In other words, data is the gold of knowledge (Kardasz *et al.*, 2022). The importance of data is emphasised by the Financial Controller of a crisp manufacturing company as:

“Sometimes getting that balance around the data analysis, especially on big data analysis, is worth investing in because you’re not quite sure what you’ll get out” (C2P1)

The notion of data is crucial for understanding what constitutes big data and, consequently, for acknowledging the different data sources. The financial controller of a meat processing company raised a pertinent point regarding the importance of paying attention to value for money when acquiring information.

“The theory of gathering all the information is good, but the capability to turn that information into value is the biggest gap in everything” (C1P1).

Since this point was raised in response to the question “what constitutes big data,” it can be assumed that they were unsure of the difference between data and information.

High Costs, Resource Allocation and Interoperability with IoT

BDA can require substantial computational power (Appelbaum, Kogan, Vasarhelyi et al., 2017; Hashem et al., 2015), which could translate into a significant financial expenditure (Sivarajah et al., 2017). Additionally, establishing and modifying organisational capabilities, including skills, procedures, processes, and structures, is costly, yet these qualities can yield substantial economic advantages (Brynjolfsson, Hitt and Kim, 2011). The declining prices of computers and storage, along with the reduced incremental cost of repetitive analytical procedures, have facilitated more frequent analytics (Appelbaum et al., 2017). Despite such a symbolic reduction in costs, companies in the agri-food and beverage industry often operate on a tight budget, and investing in these technologies may be a significant cost for them. Hence, organisations may only choose to invest in resources that have a high value-for-money ratio. Besides, the cost of implementing any new system can be substantial, especially for disruptive technologies like BDA. The Management accountant of a potato crisp processing company draws our attention to the fact that the cost of performing big data analysis may not be worth the information generated.

“Cost benefits are significant in a small or medium company” (C2P2)

The Financial Controller of a chocolate manufacturing company reiterates this assertion:

“trying to make sure that we’re tapping into an IT platform that will bring benefits and efficiency to our business” (C3P1)”

Gupta & George (2016) suggest that resources can be further subdivided into three categories: physical (such as computer hardware and software and the Internet of Things), human talents (such as the knowledge and skills of employees), and intangible (such as the culture of an organisation and the learning curve of the

company's employees). Much of the literature on information systems capabilities has extensively categorised resources into tangibles, human skills, and intangibles (Chae, Koh and Prybutok, 2014). These capabilities are made possible by the company's IT governance policies, which align with its processes and, when appropriately applied, will result in a high-quality system. Therefore, it is optimal for IT governance policies to reflect strategic organisational policies (Al-Fatlawi, Farttoosi and Almagtome, 2021).

The processing of food involves several stages, such as sourcing, production, and distribution (Irfan and Wang, 2019), and relies on a range of data sources, including sensors, ERP systems, and customer feedback (Tongsuksai and Mathrani, 2020; Karnik *et al.*, 2021). Allocating resources to each process and merging these many data sources into a unified platform may be challenging. In food production, getting the IoT to communicate with and capture the correct data from the sensors on the production machines can be particularly challenging. Thus, resources are connected to maximise control over data capture from production machines. The IT manager of a potato crisp manufacturing company confirmed the importance of interoperability between their production machines and IoT systems for capturing production data.

“So all of our machines in the factory have been linked, and they are running through an IoT device that is basically storing data for us” (C2P3).

In some circumstances where a company has acquired a sound quality system, processes may need to be changed to get the best out of new systems, as declared by the management accountant of a potato crisp producer:

“We found that [quality system] did what it did, but many of our processes had to change to map to the system” (C2P2).

It may not be easy to aggregate data from all these IoT devices, such as sensors, cameras, and wearables, because they use a variety of protocols and data formats. For example, cameras can monitor the movement of goods and supplies in and out of the production floor to ensure accountability. Similarly, wearables can monitor employee behaviour when handling food items on the production floors. Also, labour costs can

be minimised if organisations utilise IoT to monitor employee engagement, using wearables or clock-in machines. The Financial Controller of a meat processing company refer to this method of control as follows:

“Labour is a key part of our process, and it would be great if we could automate the capture of that information. We could have better information if we had more data from the tracking system throughout the factory. We had to rely on supervisors to say that Tom was there, and Mick was there, and Mary was over there. Whereas if the software captured that information, then there would be fewer errors.” (C9P1)

This control mechanism, which relies on data being captured and processed, is echoed by the CEO of a meat production company:

“What we’ve purchased from them is a fobbing system, okay, which controls the movement of people. So, in terms of discipline and control, the humans are the one, I suppose, most important part of our business to measure in terms of safety, in terms of control, in terms of honesty, in terms of our own goods and services” (C8P1)

These examples, like other devices connected to the IoT, produce enormous volumes of data, which can burden the storage and processing capacities currently available; hence, the need for effective data management and storage solutions.

6.4 Summary of Key Findings

The preceding discussions have been based on in-depth interviews with industry specialists to generate an understanding of how BDA facilitates MCS in the agri-food and beverage industry. After collecting qualitative, non-numerical data and conducting thematic analysis, I conceptualised six significant themes as key constructs for establishing the relationship between BDA and MCS. These themes include sustainability, innovation, product costing, quality assurance, performance measurement and management, and challenges.

Because personnel were involved in using BDA to facilitate MCS, it was necessary to use SST as an analytical framework to establish the BDA-MCS relationship. The conceptual framework for this study is based on the fact that data generated from the

factory floor is analysed to establish the connecting tissues linked to the outcomes. Data analytics techniques facilitate the extraction of relevant information needed to make informed decisions, given the sheer volume of data generated. These decisions are made by human agents who consider various factors (structures). It was necessary to establish the role of SST, especially in bracketing its constituent components, to show how they fit into such an analysis.

Each theme was critically analysed using quotations from the interview scripts to establish a thought process of BDA usage within the agri-food and beverage industry. It was confirmed that these technologies cannot be disconnected from the individuals' potency. Many interviewees said that incorporating sustainability into organisational strategies was the best approach to achieve it. Meanwhile, writing strategies are not enough—you must implement them. In the same way, innovation, product costing, quality assurance, and performance management all depend heavily on data from various sources. BDA techniques are crucial for turning data into information, but their use poses several challenges. Some of these challenges were identified through analysis of the interview data, and solutions will be suggested in the next chapter, including contributions and recommendations. Before presenting the contributions and recommendations from this study, it is worth summarising the findings from the discussion above. Figure 20 shows how decision-makers can use data analytics to fulfil desired operational optimisation strategies.

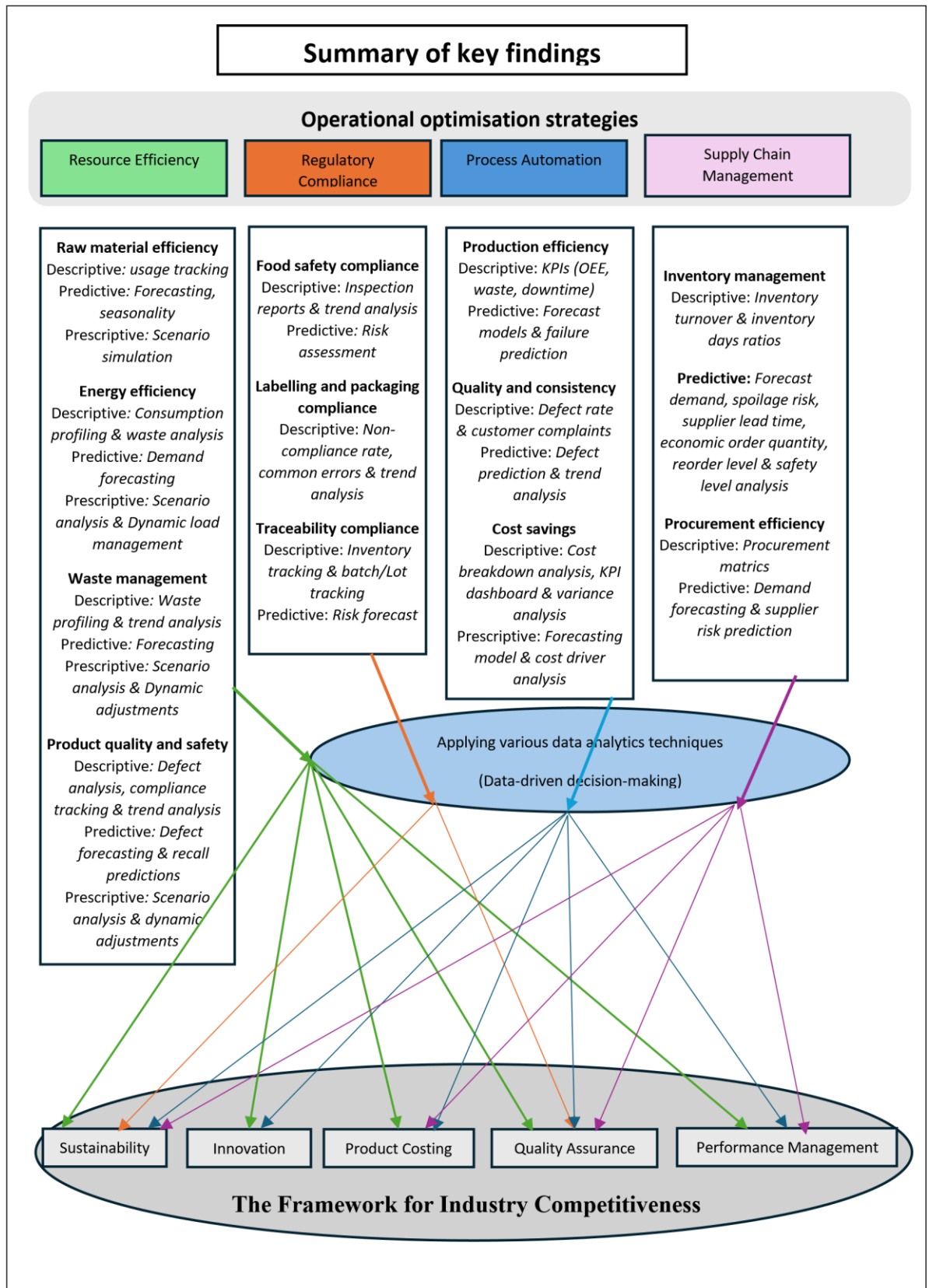


Figure 20: Summary of key findings

Operational optimisation strategies compiled from this study include resource efficiency, regulatory compliance, process automation, and supply chain optimisation.

Effective implementation of these strategies, underpinned by data-informed decisionmaking, can enable the organisation to achieve a competitive edge relative to its industry counterparts. Such success can be measured by analysing the organisation's achievements in targets often found in the agri-food and beverage industry. These objectives include sustainability, innovation, product costing, quality assurance, and performance management. The framework's impact on industry competitiveness is presented as part of the implications for stakeholders, entitled "Big Data Analytics: Informing and Enhancing MCS" (section 7.3). This research enhances SST by elucidating the co-evolution of BDA tools (as structures) and human acts (agency) within the framework of MCS, thereby expanding SST to the convergence of technology and organisational control systems.

Chapter 7 Discussion

7.1 Introduction

In this chapter, the outcomes of this work are examined on several different levels. This research was conducted to contribute to the current body of knowledge by enhancing our understanding of how data-enabled control systems operate and how this, in turn, shapes whether control practices are reinforced or changed. Stakeholders in the agri-food and beverage industry are interested in how BDA informs and enhances MCS, as well as how MCS structures determine an organisation's BDA needs. In this regard, it was vital to emphasise the utilisation of BDA to leverage management control functions within an organisation. A study of these two interlocking concepts, with humans mediating their successful implementation, requires a framework that enables the researcher to gain a deeper understanding of the issues surrounding them. SST provides a platform for appreciating the agentic challenges that arise from the use of BDA to facilitate MCS in food manufacturing companies.

The analysis focuses on three key components: (1) BDA informing and enhancing MCS, (2) the role of SST in understanding how BDA facilitates MCS and (3) linkage of prior literature to the current study.

7.2 Interpreting External Pressures with BDA-enabled Controls

7.2.1 Introduction

The study finds that agri-food organisational actors interpret external pressures (such as regulations, technologies and global supply chain) primarily through the lens of existing control logics, and that BDA-enabled systems tend to reinforce established practices when pressures are seen as non-negotiable constraints but can trigger change when actors perceive room for manoeuvre or opportunities for improvement. This study identifies resource efficiency, regulatory compliance, process automation, and supply chain management as the key areas in which BDA can facilitate MCS.

The study develops an evidence-based framework explaining how agri-food and beverage manufacturers leverage MCS functions through BDA. BDA provides the

volume, variety and timeliness of information required for effective control, enabling more accurate and responsive decision-making. By supporting theory-informed analysis of complex and uncertain situations, BDA helps organisational actors detect changes in their environment and generate decision-relevant insights. In this way, MCS increasingly incorporate predictive and prescriptive analytics that anticipate future trends and recommend actions, thereby strengthening the forward-looking and strategic dimension of control.

Within the agri-food and beverage industry, firms employ multiple operational optimisation strategies to remain competitive under cost, quality and sustainability pressures. Key pillars of operational excellence include sustainability, innovation, product costing, quality assurance and performance management. This study, in line with prior literature, identifies resource efficiency, regulatory compliance, process automation, and supply chain management as core strategies for operationalising these pillars. When combined with BDA, these strategies can improve efficiency by maximising output, reducing waste and lowering costs. From an SST perspective, these strategies represent external structures that shape the conditions of action; BDA enables organisational actors to engage with, monitor and selectively modify these structures through their day-to-day conduct.

As regulatory, technological and market demands intensify, MCS in agri-food and beverage firms are becoming more complex. This complexity is amplified by rapid advances in data and analytics technologies, which embed digital infrastructures into everyday control practices. The analysis in this section directly addresses the secondary research questions: *“How do industry-level analytical developments constitute external structural conditions that shape the use of management control practices in the agri-food and beverage industry?”* and *“How does the agency of management accountants contribute to the reproduction or transformation of control logics and data-driven decision-making practices over time?”* Both questions concern how data are mobilised to design and enact MCS, and how management accountants, as key agents, mediate the relationship between BDA capabilities and organisational control.

Historically, complex decisions relied largely on experience and basic descriptive statistics. Contemporary prescriptive analytics solutions, building on descriptive and

predictive data, allow management accountants to provide targeted, model-based decision support (Appelbaum *et al.*, 2017). Such analytics offer continually updated feedback on organisational performance and on the behavioural effects of control mechanisms. Interpreted through SST, this facilitates a richer examination of how external structures (e.g. formal controls, regulations) influence agents' conduct and how, in turn, agents' data-driven decisions reproduce or gradually transform those structures. The dynamic interplay between structure and agency becomes visible when organisations use BDA to trace how specific control designs shape behaviour and how behavioural responses prompt adjustments to controls.

Adapting MCS to evolving conditions is therefore not a linear redesign task but an iterative and exploratory process (Hartmann, Reuter and Strauss, 2023), particularly in big-data-intensive contexts where new analytical possibilities emerge faster than formal control templates can keep pace. BDA enables continuous monitoring of performance against key strategic objectives and optimisation strategies. Advanced analytics support managers in evaluating performance relative to critical metrics and in recalibrating controls based on observed patterns and anomalies (Gill *et al.*, 2022). The principal insights of this study show how data-driven decision-making contributes to achieving operational efficiency in agri-food and beverage organisations by linking BDA-enabled monitoring to the modification or reinforcement of existing control routines.

Consequently, the implications for stakeholders are derived from these findings and from the organisational strategies that underpin operational excellence in this industry (summarised in Figure 20). The following subsections examine how BDA techniques are deployed within the identified optimisation strategies and, from an SST standpoint, how organisational actors use these techniques to interpret external pressures, exercise agency, and shape the evolution of MCS.

7.2.2 Resource Efficiency

The manufacturing industry converts raw materials into finished products while relying on additional resources such as electricity, water, and labour. Consequently, improving resource efficiency is a key priority for manufacturing organisations seeking to optimise input utilisation, minimise waste, and enhance operational performance. In particular, the agri-food and beverage industry faces increasing

pressure to reduce raw material consumption, energy use, and environmental impacts while maintaining product quality and regulatory compliance. Therefore, it is logical for manufacturing organisations to focus on optimising input resources to identify opportunities to reduce raw materials, water, and energy consumption, eliminate waste, and enhance efficiency, yield, and compliance with sustainable practices (Omar, Minoufekar and Plapper, 2019).

From an SST perspective, resource-efficiency practices emerge from the interaction between organisational actors and the structural conditions in which they operate. External structures (such as regulatory requirements, sustainability standards, supply chain pressures, and technological infrastructures) condition how organisations manage resource utilisation. At the same time, internal structures, including managers' knowledge, professional norms, and analytical competencies, influence how decisionmakers interpret these structural pressures and enact management control practices. In this context, BDA technologies can be understood as socio-technical resources that actors draw upon to monitor, analyse, and optimise resource use within organisational processes.

This subsection builds on the outcome in Section 6.3.1 to expand the framework for utilising BDA to enhance resource efficiency. When decision-makers have access to accurate and timely information, they are more likely to make improved decisions regarding resource allocation and operational performance, leading to enhanced utilisation of organisational resources (Jagtap and Rahimifard, 2019). Within an SST lens, this process reflects how actors mobilise analytical capabilities as part of their internal structures when enacting management control practices. However, a major obstacle to improving resource efficiency is the lack of adequate capabilities for collecting, exchanging, and sharing real-time data among diverse stakeholders across the value chain (Jagtap and Rahimifard, 2017). Such limitations restrict actors' ability to interpret resource utilisation patterns and respond effectively to emerging operational challenges.

Consequently, developing capabilities for real-time data integration and analytics can enhance visibility and awareness of resource utilisation, enabling more informed decision-making. For example, Kenett et al. (2018) suggest that advanced manufacturing policies promoting the adoption of sensor-based Internet of Things

(IoT) systems, combined with sophisticated data analytics, can facilitate real-time monitoring of resource consumption. These technologies allow organisational actors to enact data-driven control practices that support sustainability, operational efficiency, and innovation. Within an SST framework, such technological infrastructures represent external structural resources that condition—but do not determine—how actors manage organisational processes.

The outcomes of these policies often enable organisations to strengthen their sustainability and innovation capabilities while ensuring accurate product costing and quality assurance. However, resource efficiency improvements depend not only on technological capabilities but also on how organisational actors interpret and mobilise these technologies within existing MCS. As a result, policies designed to ensure the efficient use of resources must be continuously evaluated and adjusted through ongoing organisational learning and feedback mechanisms. Effective performance management systems are therefore essential for monitoring resource utilisation and supporting corrective actions that improve operational performance over time.

Overall, this subsection provides context for how BDA techniques can support the effective utilisation of common resources in the agri-food and beverage industry. By enhancing visibility into operational processes and enabling data-driven decisionmaking, BDA can help organisations achieve key objectives, including sustainability, innovation, product-costing accuracy, quality assurance, and supply-chain efficiency. The table below maps these common organisational resources to relevant BDA techniques for evaluating and optimising their utilisation in manufacturing processes.

Raw materials	Descriptive: <i>usage tracking</i>
	Predictive: <i>Forecasting, seasonality</i>
	Prescriptive: <i>Scenario simulation</i>
Energy efficiency	Descriptive: <i>Consumption profiling & waste analysis</i>
	Predictive: <i>Demand forecasting</i>
	Prescriptive: <i>Scenario analysis & Dynamic load management</i>
	Descriptive: <i>Waste profiling & trend analysis</i>

Waste management	Predictive: <i>Forecasting</i>
	Prescriptive: <i>Scenario analysis & Dynamic adjustments</i>
Product quality and safety	Descriptive: <i>Defect analysis, compliance tracking & trend analysis</i>
	Predictive: <i>Defect forecasting & recall predictions</i>
	Prescriptive: <i>Scenario analysis & dynamic adjustments</i>

Figure 21: Potential use of BDA to facilitate resource efficiency [Source: Author]

Raw material efficiency

Evaluating raw material efficiency in agri-food and beverage companies entails using data analysis techniques to monitor, measure, and improve the utilisation of raw materials. The evaluation of raw materials efficiency can be approached from two perspectives: usage and supply chain.

The efficient use of raw materials in the agri-food and beverage industry is crucial for many reasons, including the impact of wastage on sustainability and product costing. Food wastage has been a nagging issue, frowned upon by civil society due to the increasing food shortage. From a profitability perspective, raw material wastage increases the price of the finished product, irrespective of the accounting method adopted. It is therefore necessary for agri-food and beverage companies to minimise raw material waste. Descriptive analytics can help improve usage tracking by furnishing management with insights into historical data. Additionally, diagnostic analytics can provide further insight into how and why the waste occurred. Therefore, analysing historical data on raw material usage can identify patterns, trends, and anomalies (De Wilde *et al.*, 2013). For example, a potato crisp producer monitors the tonnage of raw potatoes fed into the peeler and compares the results to the expected weight of the peeled potatoes. If the result is not as expected, then the teeth of the peeler may be checked and recalibrated. In a modern factory, most machines are connected to IoT, which reads and transmits data to the system, analysing and visualising the result on a dashboard for management to take action. With this information, management can take corrective action to prevent a recurrence of such wastage.

As mentioned in Section 6.3.1, most raw materials used in the agri-food and beverage industry are perishable, making it challenging to manage raw material inventory without incurring wastage. In addition, supply inconsistencies may arise due to seasonality and other factors, necessitating adequate storage capacity (Shurson, 2020), and inadequate storage systems may lead to increased wastage. Prescriptive analytics, guided by scenario simulation, can be used to determine the optimal quantity of raw materials required during a production run, thus minimising wastage. For example, Dadhaneeya et al. (2023) point out that raw materials must be accessible in an appropriate manner to prevent stockouts, overstocking, and waste. Similarly, participants C1P2 and C6P1 attest to ensuring that only the correct amount of inventory is held to avoid wastage (section 6.3.3).

Beyond the perishability of raw materials in the agri-food and beverage industry, seasonality often complicates raw material inventory management. Predictive analytics can assist management in forecasting raw materials demand during specific periods or seasons. Predictive analytics captures strategy changes over time and utilises an algorithm to forecast outcomes, automate decision-making, and equip management with the skills to make informed suggestions for effective strategy implementation. Therefore, the agri-food and beverage industry must accurately forecast future consumer behaviour and seasonality trends to use raw materials and other resources efficiently.

Energy efficiency

Sustainability revolves around the efficient use of resources (Rikhardsson and Dull, 2016; Awan *et al.*, 2021; Konur *et al.*, 2021). Energy is scarce, so food manufacturers must monitor their energy consumption as effectively as possible. (Konur *et al.*, 2021) suggest that today's factories are considered smart ecosystems in which humans, machines, and devices interact to produce efficient products. Through IoT integration, manufacturing processes generate enormous amounts of data that can be used to evaluate energy efficiency. When combined with diagnostic analytics, descriptive analytics can play a crucial role in elucidating consumption patterns and analysing energy waste. For example, from a profitability perspective, measuring energy consumption per product unit (kWh/unit) would contribute to a more accurate product

cost, thus recovering the cost when the product is finally sold. Meanwhile, a measure of the percentage of energy sourced from renewable sources can reassure the organisation and its stakeholders of their achievements in sustainability. As highlighted in section 6.3.1, less energy consumption implies more efficient machines, thus making the organisation's production process more sustainable.

Management can utilise predictive analytics techniques to forecast future energy demands, thereby avoiding outages during periods of high demand. Additionally, prescriptive analytical techniques, such as scenario analysis and dynamic load management, enable managers to simulate energy consumption patterns and identify them. Dynamic load management has the potential to significantly improve energy efficiency in the food processing industry by optimising energy usage patterns. Zhu and Fuli's (2023) energy efficiency gap analysis can integrate findings from an individual system's self-analysis and concurrent analysis of multiple systems to inform optimisation strategies, identify energy-saving impediments, implement targeted energy-saving enhancements, and significantly enhance energy conservation in industrial systems. Meanwhile, Virtanen et al. (2013) also suggest that the energy efficiency monitoring system should have been utilised more effectively to foster learning about environmental concerns and to share information with others. This approach to multi-system analysis is clearly articulated in the sustainability strategies of many participants, as explained in section 4.4.3. The deployment of IoT in the agrifood and beverage industry, along with the use of various BDA technologies, can help organisations drastically reduce their energy consumption. As explained in Section 6.3.1, aligning IT systems with manufacturing processes to provide the necessary data for executing the company's plans has become part of its strategic roadmap and is aligned with the business strategy. Food manufacturing companies can discover inefficiencies, optimise operations, and reduce energy costs while improving sustainability by implementing these strategies and measuring energy-efficiency indicators (Wang, 2014). The significance of data-driven decision-making and ongoing energy-efficiency enhancements in food manufacturing enterprises will make them more sustainable and competitive.

Waste management

Although sustainability assessment is crucial in helping decision-makers evaluate and improve waste management systems, innovation is at the heart of both objectives. Souza et al. (2015) posit that waste management innovation encompasses technological improvements and strategies that integrate sustainability concepts, such as creating more eco-friendly products and ensuring sustainable value across the supply chain. This stance suggests that incorporating sustainability into waste management requires new strategies that integrate environmental considerations with quality and long-term value generation. Awan et al. (2021) and Konur et al. (2021) suggest that waste management and carbon footprint reduction have a direct impact on sustainability. Consequently, numerous KPIs can be used to evaluate the effectiveness of waste management. BDA technologies can facilitate this evaluation by harnessing and processing data from various sources.

Descriptive analytics can assist organisations in examining historical waste data to identify patterns over time (daily, weekly, and seasonal trends). Once a pattern is known, decision-makers can use the information to implement actions that reduce waste. Descriptive analytics can also profile waste generation in the food manufacturing process, classified by product, production segment, or department. For example, collecting and analysing data on the types and quantities of waste allows management to identify ways to improve the amount or percentage of waste generated. In some cases, the waste may be used as a byproduct and further processed into a valuable product. Diagnostic analytics can pinpoint where and how waste is generated and, consequently, devise means (using other BDA techniques) to prevent or reduce waste in a specific area. Predictive analytics can forecast waste levels based on production schedules and historical data. As an illustration, machine learning algorithms can be utilised to forecast the likelihood of spoilage by monitoring the inventory of perishable raw materials. These algorithms take into account several key aspects, including storage conditions, shelf life, and raw material quality. A decisionmaker armed with this information may then employ the economic order quantity model to ensure the right amount of raw materials is ordered at any given time.

For other types of waste, such as packaging waste, prescriptive analytics can be used to simulate various waste management strategies and determine the most effective approach for reduction and recycling. Real-time analytics, as a form of prescriptive analytics, can also suggest process changes based on current waste-generation trends. Trevisan and Formentini (2024) suggest that supermarkets can implement AI at the retail level. When integrated with machine learning, it can analyse product data to predict the remaining time until fruits and vegetables progress to the next stage of deterioration. Agri-food and beverage companies can adopt a similar approach by implementing AI and machine learning in the warehouse to evaluate product data and forecast the remaining time until perishable raw materials or finished products reach the next stage of deterioration. This approach to eliminating waste would have a tremendous impact on product quality, as raw materials are used as fresh as possible and finished goods are sold while still fresh. Finally, given the issues encountered by the agri-food and beverage industry, employing these data analytics approaches enables food production organisations to obtain actionable insights into their waste management policies, optimise processes, and advance towards more sustainable operations.

Product quality and safety

The agri-food and beverage industry is constrained by regulations and customer demand: its products must meet required regulatory standards while ensuring customer satisfaction. That means companies operating in this industry must regularly measure and assess product quality and safety efficiency. These measurements and assessments in a food production company involve analysing compliance with safety standards, minimising defects, and ensuring consistent product quality. Mittal and Gupta (2021) assert that organisations implementing the TQM strategy undergo a transition towards defect prevention, leading to enhanced quality assurance. An organisation's productivity, quality, and competitiveness can all be improved through the use of TQM's framework, which provides a structured approach for executing significant quality initiatives. TQM provides a framework of critical success factors, including continuous improvement, customer satisfaction, employee empowerment and engagement, teamwork, process management, supplier management, commitment

from top management, education and training, benchmarking, and the application of tools and procedures (Mittal and Gupta, 2021).

The critical success factor that most significantly impacts the other factors in implementing the TQM approach is the company's ability to improve continuously. Continuous improvement relies on decision-making that is based on accurate information. Descriptive analytics can play a pivotal role in defect detection. As discussed in section 7.2.3, BDA techniques can monitor product quality in real-time and identify potential problems early, helping manufacturers prevent defects, improve overall product quality, and gain a competitive advantage. Descriptive analytics can also help manufacturers track compliance by analysing data on internal compliance issues within the company's processes before they reach critical points that could attract fines and penalties. This preventive or precautionary approach is achieved through the execution of quality controls on processes and products. As part of descriptive analytics, trend analysis can identify and monitor potential blind spots in manufacturing processes. For example, an animal that enters the slaughterhouse without its Animal Identification and Movement (AIM) number cannot proceed through the process due to potential issues with regulatory authorities. Trend analysis may help establish whether cattle from a particular farm are more likely to have their AIM number poorly printed or absent. Thus, more attention is paid to cattle from that farm to ensure the number is found before proceeding.

The use of predictive analytics allows for the forecasting of defect rates based on production schedules, equipment wear, and material variability (Lee, Cao and Ng, 2016). This forecasting is accomplished by analysing data from quality control records, maintenance logs, customer complaints, or other sources. The anticipated outcomes enable organisations to proactively manage potential issues, including preventive maintenance and resource allocation, thereby establishing systems to notify operators or maintenance staff of possible problems. On the other hand, prescriptive analytics, particularly through scenario analysis, can also help prevent future calamities. Prescriptive analytics can prescribe optimal actions to limit risks and minimise possible damage, such as resource allocation and policy modifications to enhance preparedness and response capabilities. Utilising these data analytics

approaches, food production companies can ensure high-quality and safe products while minimising costs, enhancing operations, and adhering to regulatory standards.

7.2.3 Regulatory Compliance

As stated in section 6.3.1, one of the key objectives of companies in the agri-food and beverage industry is to meet regulatory and consumer needs through transparency and traceability. Regulatory requirements to ensure food safety are stringent, preventing food producers from cutting corners, as consumers demand healthier alternatives (Lebelo *et al.*, 2021; Vriezen, Plishka and Cranfield, 2023; Rebezov *et al.*, 2024; Tran *et al.*, 2024). Therefore, food safety compliance is an aspect that any food manufacturer cannot neglect. Another challenge faced by food manufacturers is the issue of allergies, which requires impeccable labelling and packaging rules that food manufacturers must comply with (Ganderats-Fuentes and Morgan, 2023; European Court of Auditors, 2024). Traceability is also a significant challenge for food manufacturers. Consumers generally demand traceability (Vriezen, Plishka and Cranfield, 2023; Tran *et al.*, 2024), and, most importantly, in the case of contamination, the agri-food and beverage company should be able to trace back to the source (Zhou, Zhang and Wang, 2022).

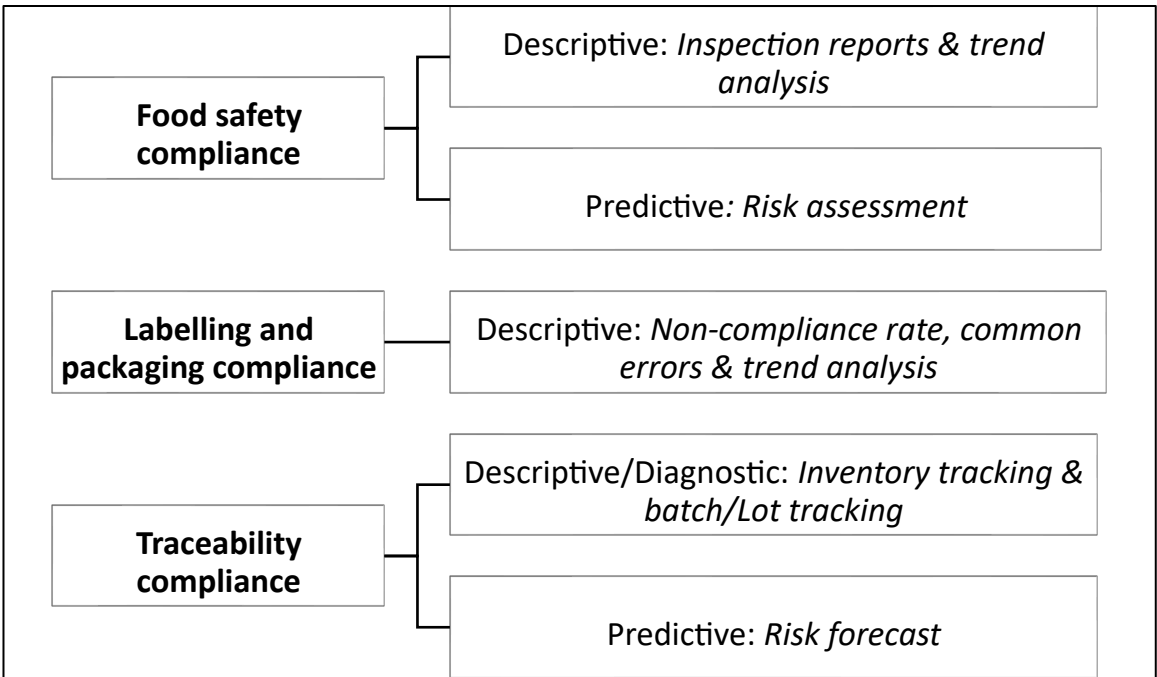


Figure 22: Potential use of BDA to facilitate regulatory compliance [Source: Author]

Food safety compliance

Food safety compliance refers to the measures and assessments essential to ensuring food quality. These assurances can be provided by inspection reports and trend analysis, which are part of descriptive analytics. Food safety compliance reports serve two primary purposes: ensuring consumer safety and ensuring adherence to regulatory requirements.

Descriptive analytics can help identify and mitigate food safety issues, prevent foodborne infections, and safeguard public health. By analysing inspection reports from previous years or from proxy companies, decision-makers can infer potential risks associated with a product in a particular company or segment in which the company operates. In the case of compliance, analysis of these inspection reports serves as proof that a food manufacturer is making an effort to comply with the requirements. Section 6.3.4 explains how adopting well-known food safety management techniques, such as Good Manufacturing Practices (GMP) and Hazard Analysis and Critical Control Points (HACCP), can bolster food quality assurance. Both techniques require proactive risk assessment and can benefit significantly from predictive analytics techniques like data mining and simulation models (Nychas *et al.*, 2021; Mu *et al.*, 2024). In general, inspection reports are essential for ensuring food safety regulations are followed. They achieve this by recording compliance, identifying hazards, promoting improvement, and ultimately protecting public health.

Labelling and packaging compliance

Section 6.3.1 explains how sustainability in agri-food and beverage companies involves adopting practices that minimise environmental impact, promote social responsibility, and ensure economic viability while producing quality food products. Compliance with labelling and packaging is one of the good practices that will reduce waste and ensure adherence to regulations. By ensuring that packaging is designed for optimal use and disposal, and by implementing proper labelling and package compliance, waste can be reduced. Clear labelling can also help consumers understand how to recycle or dispose of packaging appropriately. On the other hand, organisations that adhere to regulations evade legal consequences and maintain their positive reputation. Hence, in addition to minimising common errors, organisations must employ trend analysis to establish patterns of non-compliance to prevent recurrence.

Agri-food and beverage companies can detect persistent issues and areas with higher non-compliance rates by utilising data from various sources, including quality control logs, inspection reports, and quality management systems. Descriptive analytics can help identify specific processes or products that require improvement. Additionally, the analysis could provide a benchmark to help understand the company's noncompliance rate relative to others and identify areas for improvement. Diagnostic analytics can further aid in identifying the underlying reasons for non-compliance by examining data for common elements, thereby facilitating the implementation of corrective measures to prevent future incidents. By using these BDA techniques, organisations can help alleviate the pressure from governments and consumers by assisting in better labelling for traceability and allergies.

Traceability compliance

The primary purpose of traceability in the agri-food and beverage industry is to ensure quality. As stated in section 6.3.4, quality assurance in food and beverage products has never been more important, given the increased requirements from regulatory bodies and consumer demands. The onus is on agri-food and beverage companies to ensure they comply with the traceability regulations. Some food manufacturers may have complex supply chain systems which may trace their raw materials to jurisdictions far and wide. BDA techniques can help organisations comply with traceability requirements, regardless of the complexity of their supply chain (Mu *et al.*, 2024).

Agri-food and beverage companies can utilise descriptive analytics to enhance their ability to track products throughout the supply chain, ensuring that every product can be traced back to its origin. This analysis not only enhances the safety and quality of food but also helps ensure compliance and successfully manage any recalls. Descriptive analytics facilitate the maintenance of comprehensive records of all inventory movements, including batch or lot numbers, production dates, and supplier information, thereby ensuring that every item can be traced back to its origin. Agrifood and beverage companies can improve their traceability efforts by using predictive analytics to create safer products and run operations more efficiently. To maintain

consumer trust and comply with regulations, it is critical to take a proactive approach to risk forecasting.

7.2.4 Process Automation

Smart factories today are ecosystems that combine human intelligence with machine efficiency (Konur *et al.*, 2021). They use data and connectivity to create a manufacturing environment that is more efficient, flexible, and sustainable. As humans and machines continue to work together to improve productivity and quality, humans provide critical thinking, problem-solving, and creativity, while machines handle repetitive, precise, and high-speed tasks (Yang, Liu and Morgan, 2024). Automated systems should handle tasks such as assembly, packaging, and quality inspection, thereby reducing human error and increasing efficiency. IoT devices and sensors collect real-time data from machinery and processes, enabling improved monitoring, control, and optimisation of the manufacturing environment. As a result, the production process becomes more efficient, leading to improved quality and consistency while reducing the product's cost.

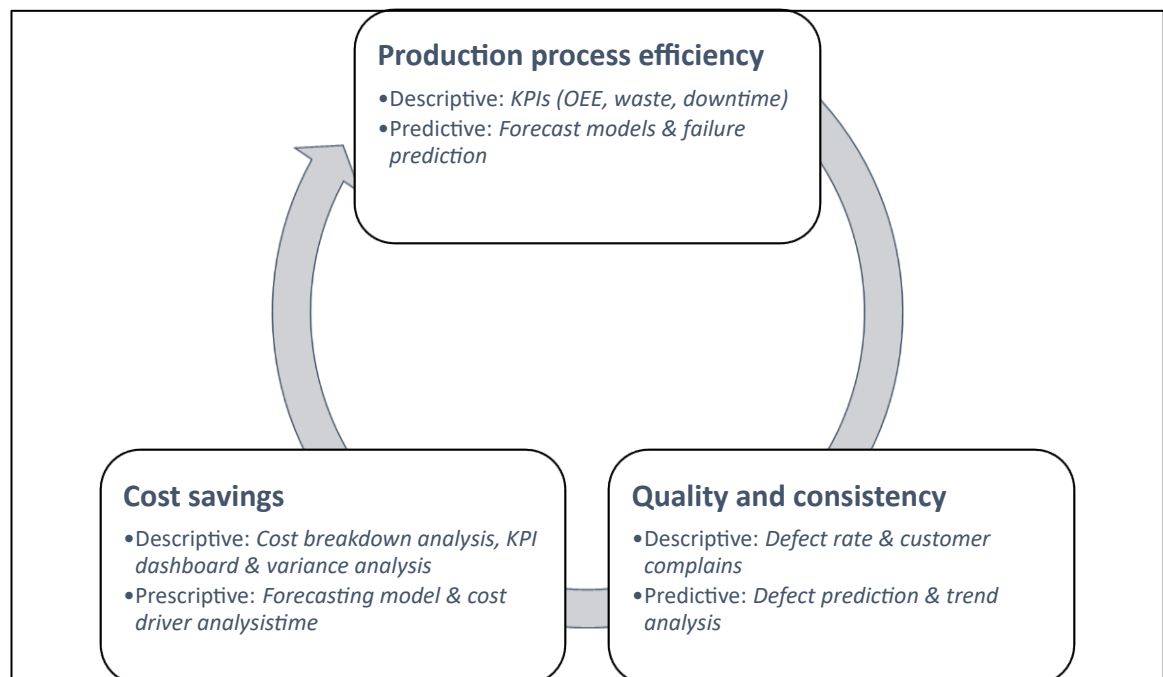


Figure 23: Potential use of BDA to facilitate process automation [Source: Author]

Production process efficiency

Production efficiency has a significant impact on agri-food and beverage companies.

Process efficiency is presented in section 6.3.4 as one of the key benefits of using BDA. It results in lower costs but also increases output and quality, thereby improving profitability and sustainability. Waste is reduced via efficient production procedures, which also decrease the amount of energy and materials used (De *et al.*, 2024). As a result, the company saves money on raw materials, labour, and utilities, eventually improving its bottom line. Jagtap and Rahimifard (2017) suggest that real-time data from product manufacturing planning systems, such as SAP and other ERP systems, could help stakeholders make more informed decisions to optimise the production process, including resource utilisation and waste reduction. In general, agri-food and beverage companies, like other manufacturing organisations, aim to achieve the highest production yield with the least downtime, provided the overall equipment effectiveness (OEE) is set at the optimal level. As a result, a food company must effectively evaluate these KPIs to stay competitive. BDA can help with this assessment in several ways.

Descriptive analytics can reveal inefficiencies and areas for improvement by analysing data on production processes and waste generation, leading to process optimisations that minimise waste and enhance overall efficiency. This analysis may uncover patterns and trends in waste generation by collecting and analysing data across various stages of production, thereby highlighting the areas with the most waste that require intervention (Bilal *et al.*, 2016). Most importantly for agri-food and beverage companies, ensuring that waste management processes adhere to regulatory requirements and industry standards can help prevent penalties and maintain a positive reputation. Also, Descriptive analytics can facilitate prompt maintenance and repairs by identifying patterns and trends in equipment performance through the collection and analysis of real-time data from production equipment (Lee, Cao and Ng, 2016; Power *et al.*, 2018). In a similar capacity, descriptive and diagnostic analytics help identify root causes and implement measures to prevent future downtime by examining historical process downtime data to pinpoint common causes and their frequency. Overall, a comprehensive understanding of a company's equipment performance will aid in identifying areas for improvement and implementing strategies to enhance OEE (Thiede, 2023).

Implementing IoT sensors and data collection systems to monitor equipment in realtime and using predictive models to detect anomalies in real-time data can prevent breakdowns. As a result, using both descriptive and predictive analytics will guarantee that the production process is efficient.

Quality and consistency

Process automation in the agri-food and beverage industry is designed to ensure the production of high-quality food products while streamlining the manufacturing process and making it more transparent and traceable. Similarly, process automation removes inconsistencies in items manufactured from different batches, such as differences in quality, flavour, and appearance. This characteristic is achievable because the process is standardised to minimise human errors. Knowing the precise amount of ingredients that go into a product is crucial in the agri-food and beverage industry. Any adjustment must be recalibrated into the machines before the next production batch. The effectiveness of process automation is often discovered from defective products or customer complaints.

Descriptive analytics can be used to establish defect rates based on historical data collected and analysed from the automated processes (Rehman *et al.*, 2019; Dai *et al.*, 2020). Similarly, customer complaints (numbers and issues) can be compiled using descriptive analytics. Through diagnostic analytics, managers can gain deeper insights into the underlying causes of issues and formulate a preventive maintenance strategy. Additionally, predictive analytics, which utilises simulation and trend analysis, can help identify issues before the product reaches customers. Consequently, manufacturers can proactively predict and rectify difficulties by examining temperature, humidity, and ingredient quality (Sections 6.3.1, 6.3.4 and 6.3.5).

Cost savings

One of the key benefits of process automation is the ability to replace manual tasks with automated systems, reducing the need for intensive manual work and lowering labour costs. Additionally, process automation ensures continuous operations with minimal errors and waste, thereby maximising production time and output. Automated processes are more efficient, saving the organisation money across the board. For example, energy-efficient technologies can be incorporated into an automated

production process, thereby reducing energy costs. Similarly, automated production procedures are likely to sustain ideal inventory levels, hence minimising holding costs and averting overstocking or stockouts.

Descriptive analytics gathers data from many sources, including financial records, invoices, and production logs (sensors, devices, networks, systems, and applications), thus facilitating the comprehensive capture of all cost components (Sarker, 2021). With all cost components in hand, a cost breakdown analysis can be conducted to identify potential cost savings. Descriptive analytics uses visualisation tools to present cost data in an easily understandable format, such as charts, graphs, and dashboards (prepopulated with KPIs). Diagnostic analysis can then be used to perform variance analysis, identifying deviations in automation production processes and investigating their causes, thereby enabling corrective actions. For organisations that use activitybased costing systems, both descriptive and prescriptive analytics can help identify the current cost drivers (descriptive) and provide insights into how to optimise and manage these costs in the future (prescriptive). Prescriptive analytics can also employ forecasting models to achieve significant cost savings, thus enhancing overall efficiency, sustainability, and profitability.

7.2.5 Supply Chain Management

Supply chain management (SCM) is a systematic progression in which an organisation manages the flow of products and services, intending to obtain maximum profit with minimum cost while fulfilling the customer's demand (Kenett, Zonnenshain and Fortuna, 2018). As explained in section 6.3.4, SCM impacts multiple facets of the agrifood and beverage industry, including efficiency, quality, traceability and sustainability. From the BDA perspective, the most influential aspects of SCM are inventory management and procurement efficiency.

Inventory management systems are crucial for ensuring food manufacturers order and hold the right amount of inventory to avoid overstocking or stockouts (using principles such as EOQ). Most ERP systems used in the agri-food and beverage industry include an inventory management module. DIOMAC is an example of a comprehensive ERP system used by some of the participants in this study. Designed specifically for the

agri-food and beverage manufacturing and distribution industries, DIOMAC offers features for real-time inventory tracking, warehouse management, and detailed reporting (Sections 4.4.3, 6.3.4, and 6.3.5). This integration helps businesses maintain accuracy in stock levels, manage orders effectively, and ensure traceability throughout the supply chain (DIOMAC, 2023). I believe that other similar ERP systems designed for the industry will generally provide similar capabilities. A typical supply chain management system aims to achieve efficient inventory management as well as ensure procurement efficiencies (Guo *et al.*, 2025).

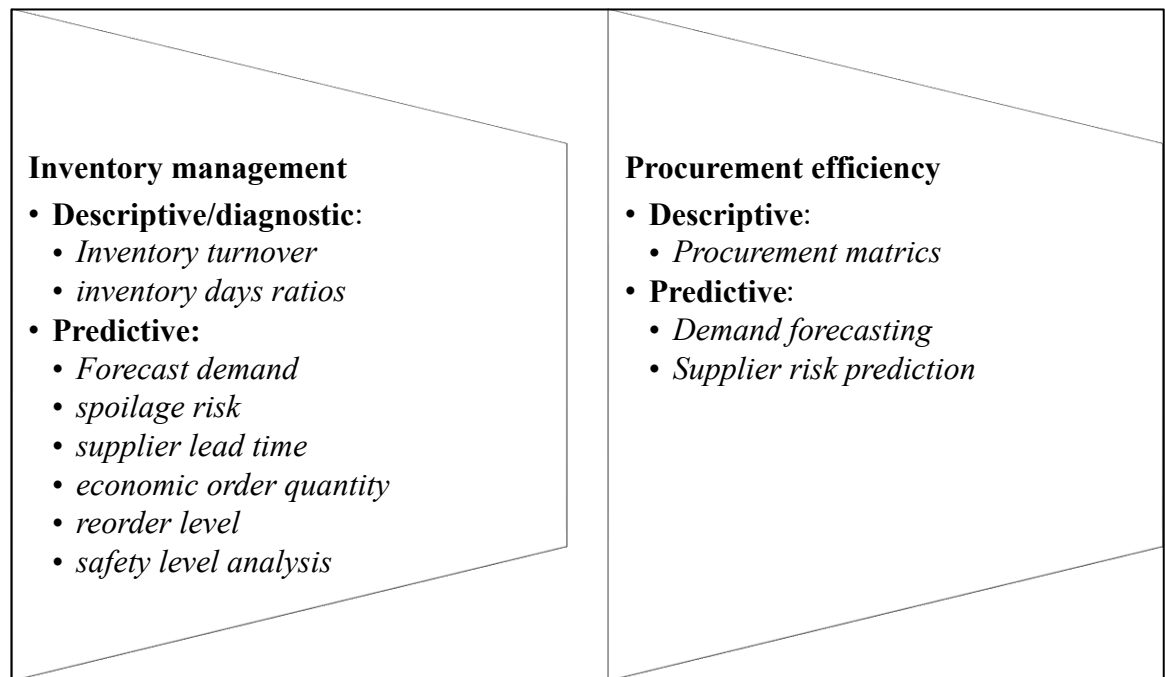


Figure 24: Potential use of BDA to facilitate supply chain management [Source: Author]

Inventory management

Inventory management is crucial for companies in the agri-food and beverage industry due to the perishable nature of some raw materials and finished goods. In other words, the implementation of specific strategies in this industry, such as sustainability, product costing and quality assurance, is contingent upon the company maintaining an effective inventory management system. Typical KPIs used to evaluate the efficiency of inventory management systems include inventory turnover, inventory days ratio, forecast demand, EOQ, and its associated elements (supplier lead time, reorder level, safety level).

The capacity of descriptive analytics to collect accurate and comprehensive datasets can help simplify calculations of inventory turnover or the inventory days ratio. Descriptive analytics can perform automatic computations and provide specific insights for different product lines or categories. Meanwhile, diagnostic analytics can use advanced algorithms to identify factors that affect performance indicators, such as sales volume, cost of goods sold (COGS), and inventory turnover or days ratio, for each product line or category.

Using predictive analytics technologies in inventory management ensures that the organisation's EOQ calculations are more accurate, adaptive, and efficient. Furthermore, predictive analytics can accurately estimate future demand by analysing historical sales data, industry trends, and other external factors. The other components of EOQ, such as supplier lead time, reorder level, and safety level, can be predicted equally well using simulations (scenario analysis) and time-series analysis.

Procurement efficiency

As part of the supply chain management system, procurement processes require optimisation to minimise expenses, strengthen supplier relationships, and promote overall operational efficiency (Whicker *et al.*, 2009). Procurement managers are required to make decisions to ensure these objectives are met with minimum deviations, and technology can help in this sense (Rahi *et al.*, 2021).

Descriptive analytics offers insights into order cycle durations and fulfilment rates, facilitating the procurement process (Roy, Spiliotopoulou and de Vries, 2022). This analytical technique also assists in identifying patterns and cost drivers, ensuring that procurement operations are financially sustainable (through budgeting and cost control). Similar to inventory management, predictive analytics can accurately estimate future demand by examining historical sales data, industry trends, and other outside influences (Syntetos *et al.*, 2016). The predictive analytics results can also enable the procurement manager to accurately anticipate and capitalise on bulk buying opportunities during promotions, ahead of demand spikes. Predictive models can minimise the impact of potential disruptions or delays, thereby minimising supplier risk.

7.3 Contextualising the use of BDA to Facilitate MCS: Using SST to structure the alliance between BDA and MCS

7.3.1 Introduction

Agri-food and beverage manufacturing is a key component of modern economies, with organisations required to ensure food safety through traceability systems (Food Safety Authority of Ireland (FSAI), 2024), a requirement that has also been welcomed by consumers (Vriezen, Plishka and Cranfield, 2023; Tran *et al.*, 2024). Although this is becoming increasingly widespread (Charlebois *et al.*, 2024), it remains challenging for food manufacturers to develop and implement systems that improve traceability. Intending to comply with regulations, food manufacturers have made significant investments in such systems. However, they are now considering using these systems as sources of management information in order to enhance their performance. Management accountants are turning to BDA to gain data-driven insights and inform their MCS. This approach is due to the enormous volume of data contained within these systems. The interviews to collect data for this study focused on topics such as "Big data in context" (which reaffirms the use of big data in the case study organisation), "BDA and its effect on MCS" (which explains how the structure of the MCS influences the use of BDA), and "Barriers to effective use of BDA within the MCS." SST facilitated the results presented in Chapter Six and the subsequent discussion. The analysis in this section directly addresses the secondary research questions: *"How do organisational actors draw upon Big Data Analytics within their internal structures when implementing management control practices?"* and *"How do organisations' position–practice relations enable or constrain the use of BDA-enabled MCS?"*. These questions seek to explain the role of those charged with using BDA to facilitate MCS, and the influence of organisational strategies on the success or failure of the relationship between BDA and MCS.

The methodology is based on Stones (2005) and Kennedy, O’Gorman and Lee (2021). The manner in which BDA data is evaluated and utilised in the agri-food and beverage industry is contingent upon the particulars of the external structures (for example, the compliance criteria established by FSAI) and the internal structures (for example, organisational structures and strategic fit), as comprehended by the many agents who make use of BDA. It is the agent's perception that these structures, both internal and

external, affect their utilisation of BDA within the MCS. Within the majority of the businesses that were investigated, the objective was to collect responses from several individuals who came from a variety of backgrounds, including financial controllers, information technology specialists, and management accountants, to gain a more thorough understanding of how the structures within the industry and the organisation led to the implementation of BDA. An agent-in-focus is focused on the agent and its interpretations and is concerned with analysing how the agent makes sense of circumstances and interprets structures. They utilise their knowledge and abilities. By conducting this analysis, the alternatives available to the agent-in-focus, as well as the constraints imposed upon them, are identified (Coad et al., 2016; Jack, 2017). By ensuring that multiple perspectives within the organisation are utilised, our objective is to distinguish between the "independent causal influences" that affect the agent-in-focus and the "irresistible causal forces" that the agent-in-focus may be able to work with or resist. This distinction recognises that different agents may perceive the same phenomenon in different ways.

The concept of agent-in-situ examines how the agent is influenced by the environment's preexisting rules, resources, and schemas, as well as how the agent interacts with these elements (Coad and Herbert, 2009; Englund and Gerdin, 2011). The focus of this approach is on the agent's location within the social structure. In this manner, the function of management accountants in utilising BDA to facilitate MCS is considered. In analysing the application of BDA in agri-food and beverage companies, an agent-in-situ approach investigates how the management accountant interacts with BDA and how their internal and external structures would differ from those of the financial controller. As a result, their agency to transform is diminished, and their primary imperative is to reproduce, although we find evidence of these individuals "breaking the mould" and being innovative.

"We now do crisp bags for airlines, a much smaller crisp bag. So, when we developed the last expansion in the factory, we installed the sizing system, which separates small crisps into small bags and big crisps into bigger bags. This makes it look better and seals better. So once we knew that there was a market for that, we changed the factory

to ensure that we could size crisps, and that's where the whole idea of agility and innovation comes" (C2P1)

In contrast to the analysis of the agent as a product of the structure, referred to as agent-in-situ, the term "agent-in-focus" refers to the analysis of the agent as an active agent within the structure. The study focuses on the agent-in-focus when analysing the usage of BDA in agri-food and beverage companies. This technique investigates how a financial controller might develop innovative ways to access and evaluate production data as part of their MCS. Part of the objectives of this study is to investigate the reasons financial controllers use data (such as to improve efficiency or identify safety concerns), their specific interpretations of the data based on their experience, and how they attempt to alter production processes based on their insights. The financial controller occupies a prominent position within the social network and has the authority to make decisions that affect other agents, given their status as agents-in-focus in this investigation.

According to this study, the financial controller is involved in decision-making regarding investments in information technology for data collection and analysis. While this happens, the management accountant uses available resources to collect and analyse data from the production floors. This analysis aligns with the financial controller's decisions and the MCS's more comprehensive structure.

7.3.2 Human agency and organisational systems in agri-food and beverage manufacturing: Navigating duality of structure

Structuration theory, developed by Anthony Giddens, describes how human agency and social structures (such as MCS) interact. Structuration Theory explains the reciprocal influence of MCS and organisational behaviour (Englund, Gerdin and Burns, 2011; Kennedy, O’Gorman and Lee, 2021). This correlation offers a theoretical framework for understanding the reciprocal interplay between MCS and organisational practices. According to the theory, the structures that exist inside an organisation, including routines, norms, and systems, both have an impact on and are impacted by the activities of the people who work in that organisation (Stones, 2005). Thus, control systems are generated not just by the acts of the individuals present in an organisation

but also by those people's actions, a relationship Giddens (1984) referred to as the duality of structure. When this concept is applied to MCS, it can be said that these systems are not imposed from the top down to control and monitor performance. Instead, they are viewed as dynamic frameworks that evolve through ongoing interaction between employees and organisational structures.

The concept of duality of structure is not as straightforward in the agri-food and beverage industry due to the complexity of the stakeholders involved. It is not just about organisations in this industry setting up rules, norms and systems (structures) for their employees to follow (agents). However, external forces also define some of these structures. Additionally, not all agents have the same capacity to act on the structures, whether to implement or modify them. Given this level of complexity in this situation, Stones' (2005) SST provides a more precise methodology for researchers to analyse specific cases. As explained in section 4.4, Stones (2005) expands the duality of structures to a quadripartite framework, which breaks down the analysis into four key elements: external structures (the broader context that shapes action), internal structures (agents' knowledge, dispositions, and interpretive frameworks), active agency (how agents actively engage with structures), and outcomes (the results of agents' actions, which may reproduce or transform structures).

The quadripartite framework provides a means to navigate and identify the nuances that encourage or inhibit the use of BDA technologies to facilitate MCS in the agrifood and beverage industry. The connecting tissues that explain how BDA technologies facilitate MCS can be established by building on the SST analytical approach presented in section 4.4. This analytical approach is rooted in the original principle of the duality of structure, which has been expanded into a quadripartite framework. The external structures (rules, regulations, and customer demands) define the internal structure (the company's strategies and organisational structure), which, in turn, impacts the agency (the behaviour of employees and management) to achieve outcomes. This approach can also be reversed, starting from agents' context analysis and proceeding to outcomes. The effectiveness of organisational operations depends on the outcomes they aim to achieve and the resources needed to achieve them. Similarly, agri-food and beverage companies can modify the external structure by

doing unique things that influence it. For example, a large food producer with substantial purchasing power can influence suppliers by establishing quality, pricing, and delivery criteria.

Analysing the agent's context is crucial for better understanding the relationship between external and internal structures. In other words, a complete MCS cycle starts with the expectations of the organisation (imposed by the external structures), followed by resources provided by the organisation to facilitate the agent's tasks (general dispositions) and the agent's knowledge of the situation under consideration (situational knowledge), leading to the expected outcomes. Building on Stones' quadripartite framework, four key pillars that impact the use of BDA to facilitate MCS in the agri-food and beverage industry include:

- 1) Agents' context analysis: External drivers and delimiters in the agri-food and beverage industry
- 2) General dispositions: Internal strategies of the organisation
- 3) Situational knowledge of the agent: Resources available
- 4) Expected outcomes

7.3.3 The Anatomy of Food Manufacturing: How Internal Structure Shapes Outcomes

Stones present external structures that supply agents with the conditions they need to act. He refers to them as “independent forces and pressuring conditions that limit the freedom of agents to do otherwise” (p. 109). In this light, he distinguishes between independent causal influences and situations where the external structures have complete autonomy over the agents they affect. However, they may directly impact the agent's life, as well as irresistible causal factors, which are situations in which the agent can reject an external influence but thinks that they are unable to do so. “The label of irresistible causal forces is more accurate than independent causal influence” (p. 111). In the agri-food and beverage industry, external forces such as regulations imposed by regulatory bodies (e.g., FSA) are considered irresistible. Food manufacturers would like to avoid some regulations to reduce costs, but they are compelled by law not to cut corners, as the consequences can be more costly than the costs they seek to reduce in the first place.

Food safety regulations are essential to the agri-food and beverage industry because of the risk its products pose to consumers. The Food Authority of Ireland implements regulations, partly in response to the EU food safety set, to monitor standards that guarantee the food safety of all European citizens. For example, EU legislation requires that food businesses in all member states must implement a Food Safety Management System based on HACCP principles (Charalambous *et al.*, 2015). Similar standards exist worldwide, with the primary aim of ensuring that local populations consume the safest products. Likewise, environmental regulations are intended to ensure that industry waste is treated and disposed of in a way that minimises environmental damage. While the agri-food and beverage industry is generally perceived as not generating much toxic waste, even non-toxic waste still needs to follow proper disposal standards. The primary source of toxic waste in this industry is processes such as the use of chemicals for rigorous cleaning to meet hygiene standards, as well as the presence of harmful microorganisms from raw materials, including pathogens (Samant, Pandey and Pandey, 2018; Lebelo *et al.*, 2021). In limited situations, hazardous byproducts may emanate from specific processes, such as slaughterhouses and meat processing plants, that generate blood and fat that can release harmful pathogens and toxins if not properly treated (Jayathilakan *et al.*, 2012; Ovuru *et al.*, 2024).

In addition to regulations and rules, economic factors beyond the industry's control also influence the MCS of companies operating in this industry. For example, customers are becoming increasingly health-conscious and demanding healthier food products, such as those made from plant-based and organic ingredients. Agri-food and beverage companies must adhere to this demand to maintain a competitive advantage in a highly competitive industry. Additionally, on the economic front, global supply chains and trade agreements impact MCS, as companies must navigate the constraints imposed by these external factors.

Finally, advances in technology also pose additional challenges for MCS as organisations scramble to keep up with these rapid developments. For example, automation in production lines is becoming the norm in most manufacturing industries, where robots can perform repetitive tasks. Similarly, software systems can

be utilised to manage inventory, control quality, and optimise supply chain management to ensure a timely and cost-effective supply of high-quality materials. The dilemma with software acquisition is determining the right package that delivers value for money. A software system used by one participant organisation epitomises an ERP system suited to the agri-food and beverage industry, as it encompasses all the necessary modules to capture and analyse data from every source within the industry. The system is fully integrated with IoT, CRM, and visualisation, and, most importantly, is customisable to suit individual needs.

The food manufacturer can flip the above external structures in various ways. For example, when food manufacturers develop new products in response to consumer demand for healthier options, the latest product might further shape consumer expectations and industry standards (Stanton, 2019; Guiné *et al.*, 2020). By influencing consumer preferences, this new product line may establish a new industry standard, reinforcing the trend toward healthier food options. Thus, agri-food and beverage companies must be innovative to meet current demands, but they may ultimately surpass these standards, thereby setting new benchmarks for the future. This recursive relationship forms part of the primary foundation of SST. A key component of this approach is understanding the practices of resignification and their recursive nature, which Giddens refers to as the structure-teaching agents who help form the structure in a circular process he calls "structuration" (Giddens, 2005).

Adhering to the external structure or taking actions that might modify it depends on the resources available to those concerned and their willingness to use them to the best of their ability. One of the highlights of SST is that it clearly distinguishes between external structures (such as regulators, market conditions, cultural norms, and technology) and internal structures (such as agents' knowledge, beliefs, and dispositions). This distinction enables a more detailed analysis of how agents read and respond to external structures, depending on their internal frameworks and values. Stones' framework divides the internal structure into two interrelated concepts that help explain how agents navigate and influence social structures: (a) general dispositions and (b) situational knowledge of the agent.

Influence of technological adoption on the agent's habits (general disposition)

Stones (2005: 87) describes general dispositions as the “internal structures that deal with the agent's habits, generalisable and transposable skills and dispositions, including their general world views, cultural schemas, characterised recipes of action and habits of speech and gesture”. Orlikowski (1992) suggests that through the consistent actions of knowledgeable and reflective individuals, interaction patterns are established as standardised practices within organisations, such as methods for manufacturing a product, coordinating meetings, or evaluating employees. Habits are considered broader, more stable patterns of thought and behaviour that guide how agents interpret and respond to situations (Mercuur, Dignum and Jonker, 2020). In line with Rose and Hackney (2003), the taken-for-granted character of the vast bulk of day-to-day MCS activities is considered a habit.

As explained in section 6.2, General dispositions refer to ingrained habits and dispositions shaped by long-term socialisation. Therefore, employees in the agri-food and beverage industry must be fully aware of the strategies to ensure adherence to food safety standards. It is best practice to articulate the most pertinent strategies through the company's vision and mission statements; however, their effectiveness must be regularly reviewed to ensure continuous adherence. This disposition is not linked to a particular setting but embodies an agent's broader worldview, values, and habitual behaviours. An organisation in the agri-food and beverage industry may have a wide range of characteristics, including a long-term commitment to sustainability, a culture of innovation, or a tendency to avoid taking risks when making decisions. These dispositions affect organisations' handling of various issues, regardless of the specific context. As demonstrated in Section 6.3, participants' vision encompasses sustainability, innovation, product costing, quality assurance, and performance management.

Although automation is expected to optimise food manufacturing processes and minimise downtime, it also brings many challenges. No matter the level of automation, humans are still required to operate the robots. Therefore, the effectiveness of automated processes depends on the operators' ability to learn quickly. The organisational culture plays a key role in achieving this learning curve. For example,

if an organisation's corporate culture focuses on shared values and norms such as innovation, sustainability, or cost efficiency, its automated processes will be more efficient. Additionally, the type of controls within the organisation can impact the learning process. From section 6.3.1, it was established that effective controls may stifle innovation and, consequently, sustainability. At the same time, sustainability is a product of effective controls on resource distribution. Therefore, management controls should be sufficiently rigid to meet organisational goals while allowing sufficient room for innovation.

Meanwhile, internal adoption of new technologies can also influence external structures by creating new competitive dynamics (El-Haddadeh, 2020). For example, the use of advanced technologies like BDA in supply chain management can lead to industry-wide adoption, and the development of new regulatory requirements for traceability may be triggered. Hence, the bidirectional application of SST, with the external structure being influenced by changes in the internal structures. This point also confirms how technology may influence MCS design as much as MCS structure influences the organisation's technological requirements.

Agent's ability to adapt to the impact of technology (Situationally specific knowledge)

Based on Giddens (1984: 75), "the structural properties of social systems are both medium and outcome of the practice they recursively organise". As a result of the data that they analyse and the behaviours they monitor, the systems used to control and manage the organisation are constantly evolving in the context of MCS. This evolution is due to their continual monitoring. The continual provision of feedback that can enhance these systems is one way in which analysing vast volumes of data contributes to the process. Two processes occur at this location: reproduction and transformation. When viewed from this perspective, one can gain insight into how social systems are replicated over time and how agents can serve as catalysts for change.

Agents are the individuals or groups who act within these structures, making decisions and influencing outcomes (Giddens, 2005). Agents draw from their dispositions (skills learned over time or instructions passed down through organisational policies) to influence outcomes. Similar to Feeney and Pierce (2016), the active agency of the individual, as applied in MCS, demonstrates the collaboration of internal and external

systems, in which the active agency offers its perspective on utilising BDA to facilitate MCS. For example, within the agri-food and beverage industry, factory workers may follow (or challenge) data-capturing procedures from the IoT during production, or the IT manager may enforce (or defy) data integrity rules. In both cases, the level of compliance depends on two main factors: the instructions or training at their disposal (including training, change management processes, organisational culture, and management attitude) and the individuals' willingness to follow the instructions (level of education, age, job satisfaction, and other personal traits).

When individuals' flexibility is restricted, MCS can both empower and restrain them. The establishment of clear regulations and guidelines is how this objective is attained. The use of BDA, which may reveal how employees perceive and utilise these technologies, enables the modification of these systems to strike a balance between control and autonomy. Power dynamics greatly influence the agent's ability to adapt to the effects of new technology. Stones discusses in detail the power dynamics and inequalities that arise when examining how agents' positions in social systems (for example, class, gender, and organisational hierarchy) influence their ability to act and shape structures. In this way, Stones places greater emphasis on active agency and position-practice relations. Active agency emphasises agents' interpretation, negotiation, and occasional rejection of external structures. On the other hand, position-practice relations examine how agents' positions within social systems (for example, roles and hierarchies) influence their ability to act and shape structures.

Additionally, a manager's disposition toward integrating technology into manufacturing processes to improve efficiency (internal structure) influences their decision to invest in IoT, even if it increases costs. This decision, in turn, may shape the company's practices and influence broader industry norms (external structures). Meanwhile, factory floor workers cannot make such decisions, as they do not have the authority to do so. However, they might make recommendations to the line manager, depending on the manager's disposition toward taking recommendations from subordinates (organisational culture).

This study has aimed to understand the interplay between agency (individual or group actions) and structure (social systems, rules, and resources) in shaping outcomes. SST has proven beneficial for examining the dynamic, recursive interplay among technology, human agency, and organisational structures to assess the potential effects of employing BDA to enhance MCS.

7.3.4 Reinforcement and Transforming Food Manufacturing: Expected Outcomes from SST Analysis

SST provides a framework for understanding how agency (individual behaviours) and structure interact to influence results. When used in conjunction with BDA to support MCS, SST provides a framework for examining the dynamic, recursive interplay among technology, human agency, and organisational structures. As explained earlier, the concept of structuration is predicated on the assumption that structures are both the medium through which social behaviours are expressed and the effect of such behaviours. To achieve the expected outcomes, the active agent engages with the structures in a process that Stones describes as “active agency”. As explained in section 4.4.5, the results of agents' actions may affect the structures in terms of reproduction or transformation.

Meanwhile, outcomes could be reproductive, which involves perpetuating or reproducing existing organisational structures, practices, and norms (Stones, 2005). The active agency roles in this study include the financial controller, the management accountant and the IT management. These roles are explained in section 4.4.3, and their impact on the structure is described in sections 4.4.4 and 6.2. The outcomes are articulated around the framework developed from findings (Figure 20), emphasising their reproductive or transformative effects on the structure.

BDA enables real-time data processing and predictive analytics, enabling managers to make data-driven decisions. As managers use BDA tools to interpret data and enhance control systems, BDA becomes embedded in the organisational structure, shaping norms and rules for decision-making. Due to the recursive relationship between BDA (agency) and organisational strategies (structure), the use of BDA leads to more adaptive and responsive MCS. This study has compiled KPIs essential to the success of the agri-food and beverage industry. These KPIs will be enhanced when industry

managers maximise the use of BDA to enable MCS (data-driven decision-making). These KPIs include sustainability, innovation, product costing, quality assurance, and performance management (Figure 20).

Sustainability (6.3.1)

Sustainability is a must, not merely a trend, for the agri-food and beverage industry. By integrating sustainable practices, companies can reduce costs, enhance brand recognition, comply with regulatory requirements, and contribute to a healthier world. Sustainability has the potential to convert the industry into a more resilient, efficient, and ethical framework that benefits businesses, consumers, and the environment concurrently. Achieving sustainability in the agri-food and beverage industry involves implementing practices that reduce environmental impact, conserve resources, and promote social and economic well-being. These objectives often include managing resources efficiently and ensuring regulatory compliance. It also requires automating manufacturing processes and implementing efficient supply chain management systems. BDA can assist with this objective by sourcing and analysing data to generate information needed to evaluate KPIs linked to the success of sustainability endeavours. Examples of efficient resource use include energy efficiency measures, waste management, and raw material efficiency. Additionally, traceability and proper labelling contribute to food safety compliance by ensuring that consumers and compliance inspectors receive accurate information about the product.

Automation is a key ingredient for Green Manufacturing Processes (GMP), which improves production efficiency (Yuan and Zhang, 2013), consequently saving costs and assuring product quality. They find that the quantitative characterisation of green manufacturing processes necessitates the use of sensors to monitor and analyse the diverse flows involved. Yuan and Zhang (2013) suggest that software solutions are required to automate data monitoring, given the complexity of managing and interpreting sensor data. Hence, there is a need for BDA technology to synthesise the data to generate the appropriate information. Agri-food and beverage companies rely on a timely supply of raw materials (mostly perishable) and therefore require an efficient supply chain management system to compete and keep up with regulations.

BDA technologies can ensure efficient inventory management by forecasting demand and reducing supplier risk and other factors linked to the EOQ model.

Innovation (6.3.2)

Innovation has the potential to enhance the agri-food and beverage industry by optimising current processes and products, thereby making them more efficient, sustainable, and aligned with consumer preferences. Concurrently, innovation has the potential to revolutionise the industry through the introduction of disruptive technologies, novel business models, and practices that effectively tackle global challenges (Wang *et al.*, 2016) while simultaneously generating new product offerings (Omar, Minoufekar and Plapper, 2019). Implementing advanced robotics for tasks like packaging, sorting, and palletising improves operational efficiency and reduces labour costs. Additionally, using IoT sensors to predict equipment failures can significantly minimise downtime and maintenance costs.

On a transformative scale, advancements in AI-driven forecasting are making smart factories increasingly prevalent. Digital twinning is a concept that impacts most innovation initiatives, such as process, product, and supply chain innovation. The concept of digital twins is the accurate digital replication of a physical system that acts as its virtual counterpart (Raja Santhi and Muthuswamy, 2023). They provide an example of the core concept of twinning, using data gathered from the original model and mirroring it in its replicate model to simulate and understand real-time behaviour. Advancements in AI have led to diverse applications of digital twins in manufacturing, encompassing product design and development, manufacturing processes, asset management, process monitoring and optimisation, quality control, predictive maintenance, supply chain management, and facilitating decision-making through cross-functional collaboration among engineering, manufacturing, marketing, and sales (Raja Santhi and Muthuswamy, 2023).

Digitalisation and intelligent manufacturing are elevating the food production industry to unprecedented levels of efficiency. The integration of IoT, AI, and BDA (Industry 4.0) into manufacturing processes creates "smart factories" that enhance production efficiency in real-time. This optimisation ensures the most effective utilisation of

resources and sustains efficiency in the supply chain management system, which more precisely forecasts customer demand, thereby minimising overproduction and waste.

Product costing (6.3.3)

Product costing is pivotal in enhancing and transforming the agri-food and beverage industry by offering insights into cost structures, boosting profitability, and facilitating strategic decision-making. When executed effectively, product costing has the potential to enhance efficiency, promote sustainability, and foster innovation (BosBrouwers, 2010). Accurate product costing enables manufacturers to identify areas of significant expenditure, such as raw materials, labour, and energy, thereby facilitating targeted cost-reduction strategies. Manufacturing companies must understand the actual cost of products to ensure that high-margin products receive sufficient investment, enabling more effective resource allocation. Knowing the accurate product cost can also help identify process inefficiencies and implement lean manufacturing principles to reduce waste and improve productivity.

While many businesses now use tools such as activity-based costing, target costing, functional costing, life cycle costing, and strategic cost analysis, their usefulness in increasingly digitalised environments warrants reconsideration (Bhimani and Willcocks, 2014). These novel management accounting approaches have emerged in response to the increased complexity among business objectives, operational processes, and decision-making (Bhimani, 2020). Activity-based costing relies on accurately identifying and measuring cost drivers and will benefit from accurate data collection and analysis using BDA tools. Meanwhile, target costing can benefit from using BDA technologies by collating information from different departments to help narrow the gap between the target and actual cost per unit, thereby informing decisions on whether to make or abandon a new product. Conversely, forecasting methodologies can help determine post-production expenses during a product's design stage, particularly for its end-of-life phase. A food company may utilise data across several activities and channels to enhance assortment planning and product lifecycle management (Stahl, Stein and Flath, 2021). Understanding product lifecycle costs enables food manufacturers to select sustainable materials and energy-efficient methods across the product lifecycle, from procurement to disposal.

One of the key applications of product costing is determining the selling price, particularly when a cost-plus method is employed. Due to industry competitiveness, accurate costing ensures products are competitively priced while maintaining profitability (the correct margin applied), helping manufacturers remain relevant in such a competitive market. Since customers will not want more than it costs to make the product (Wansink and Love, 2014), understanding the cost structure of each product allows companies to focus on high-margin products while phasing out lowmargin or loss-making products. According to Onat (2023), costing data enables businesses to strike a balance between quality and price, ensuring that products meet consumer expectations while remaining profitable. Food makers, for example, can provide unique solutions without incurring significant costs if they fully grasp the financial implications of personalisation, such as personalised nutrition or packaging. From a planning perspective, product costing enables precise budgeting and financial forecasting, facilitating improved strategic planning. Variances, on the other hand, facilitate performance measurement and identify areas for improvement. For example, accurate costing gives the organisation a competitive advantage when negotiating with suppliers, assuring better raw material pricing and lower input expenses.

These strategic decision-making challenges rely on accurate information and can be simplified using BDA technologies. Innovations in digital costing instruments, including software and analytical platforms, now enable real-time costing, thereby enhancing precision and informed decision-making. Advances in AI and predictive analytics enable AI-driven costing models to forecast future cost patterns, including fluctuations in raw material prices, thereby facilitating proactive adjustments. Integrating product costing with ERP systems such as the one mentioned by the case participants offers a comprehensive perspective on operations, improving efficiency and control.

Quality assurance (6.3.4)

Quality assurance (QA) is fundamental to the agri-food and beverage industry, ensuring that products meet safety, regulatory, and consumer expectations. According to Rikhardsson and Dull (2016), BDA has the potential to improve product quality assurance significantly in the agri-food and beverage industry by providing more

indepth insights, enhancing process efficiency, and facilitating proactive decisionmaking. QA may strengthen and transform the industry by improving product quality, fostering consumer trust, and enhancing operational efficiency (Maljugić *et al.*, 2024). QA is a transformative force in the agri-food and beverage industry, driving safety, efficiency, and innovation while building consumer trust and brand reputation. Manufacturing companies can achieve consistent quality, decrease risks, and open new growth prospects by incorporating QA into all operations (from raw material acquisition to production and distribution).

Food quality assurance is a primary concern for both food regulators and customers. QA systems ensure that food manufacturers adhere to local and international food safety guidelines, thereby reducing the risk of legal penalties and recalls. The Irish FSA mandates that food manufacturers adhere to hazard control standards such as HACCP, while the BDA assists them in assessing their level of compliance or identifying deficiencies. To ensure safe products, food manufacturers must implement QA procedures throughout the manufacturing process to identify and reduce potential biological, chemical, and physical hazards. The output of QA systems may include end-to-end traceability, enabling food manufacturers to promptly detect and resolve supply chain issues.

Additionally, implementing transparency practices such as clear labelling, certifications, and open communication about sourcing and production fosters consumer confidence. This practice can foster consumer loyalty and trust in the brand, while also helping to prevent product recalls. Quality assurance processes are pivotal in advanced manufacturing, also known as Industry 4.0, facilitating the evolution of production and quality conceptual frameworks, including inspection, process enhancement, and quality by design (Kenett, Zonnenshain and Fortuna, 2018). Establishing higher quality assurance standards facilitates more efficient manufacturing, resulting in cost reductions through fewer reworks, fewer errors, and fewer delays, as well as more effective utilisation of time and resources. In addition, QA methods can aid in identifying and rectifying inefficiencies that contribute to food waste, promoting recyclable packaging, and reducing energy consumption, thereby supporting sustainability objectives.

While AI and machine learning can automate quality checks, allowing for rapid corrective measures, IoT sensors provide real-time monitoring of manufacturing processes, thereby enhancing accuracy and efficiency. While QA offers significant advantages, its application in the agri-food and beverage industry encounters several obstacles, including reconciling QA expenditures with profitability, adapting QA systems to rapidly evolving legislation and consumer preferences, and maintaining consistency throughout global supply chains. Reinforcing and transforming the industry in the years to come will depend primarily on adopting cutting-edge technologies, fostering a culture of continuous improvement, and aligning QA with sustainability objectives (Maljugić *et al.*, 2024).

Performance management (6.3.5)

Strategic performance management is observing, assessing, and enhancing an organisation's operations, staff performance, and process effectiveness (Grigore, Bâgu and Radu, 2009). Food manufacturing processes are based on the organisation's operations, which must align with its strategies, and employee success is dependent on these two principles. The strategic performance management of a company is a complex and challenging process (Zamecnik and Rajnoha, 2015) that necessitates an approach that acknowledges the significance of focusing on both outcomes and the methods employed to achieve these outcomes (Kloot and Martin, 2000). Good performance management can support and transform the agri-food and beverage industry by increasing production, ensuring quality, promoting innovation, and aligning organisational goals with sustainability and profitability.

Performance management, like other MCS components, relies on high-quality data and the ability to extract accurate information to set or evaluate KPIs. Ashrafi *et al.* (2019) and Reinking *et al.* (2020) find that MCS calls for high-quality data collection to assess the application and efficient use of corporate performance management systems. BDA technology can assist in the data collection and analysis to achieve this objective. Performance management enhances operational efficiency and product quality, ultimately ensuring customer satisfaction. TQM has gained popularity due to several studies validating its impact on performance and quality. Diverse TQM

concepts influence corporate performance metrics such as quality, cost, productivity, delivery, and customer satisfaction (Mittal and Gupta, 2021).

The potential for real-time observation, combined with the growing adoption of IoT in the agri-food and beverage industry, has made performance management more efficient. Businesses can utilise dashboards and data visualisation tools to monitor parameters such as production output, equipment utilisation, and inventory levels, allowing them to make informed decisions in real-time (Kumar, K and Aithal, 2023). In principle, performance management impacts every aspect of food manufacturing, from procuring the right raw materials to ensuring customer and societal satisfaction with the product. Performance management can benefit from BDA technology. The characteristics of big data make it an indispensable tool for data-centric decisionmakers because information is the foundation of every decision. MCS can be linked to BDA through what Vitt et al. (2002) describe as opportunity areas. “In business terms, an opportunity area is a consistent set of requirements for a group of users that can be accommodated more or less from the same end-to-end system structures or solution” (Vitt et al., 2002: 128).

Section Summary

There is a possibility that big data will make MCS more agile, allowing for real-time adjustments to both strategy and controls. This agility is essential for success in an environment that is constantly changing and requires rapid responses to market fluctuations. SST provides a framework for understanding how organisational practices influence real-time changes. Furthermore, the deployment of data analytics can promote operational flexibility by improving and calibrating business processes. This deployment can further enhance operational flexibility. The capacity of these organisations to respond to environmental changes with optimal decisions in a timely manner and at lower cost than their competitors is subsequently enhanced. (Ghasemaghaei, Hassanein and Turel, 2017).

7.4 Revisiting prior literature on the use of BDA in MCS

7.4.1. Introduction

This discussion arises from a systematic literature review that identifies common themes and outlines future research directions at the intersection of BDA and MCS

(Chapters 2 and 3). The discussion begins with an analysis of how the findings from this study relate to themes identified in the literature review. This discussion helps establish a holistic framework (Figure 20) based on the themes identified from the literature and those emerging from this study.

7.4.2 BDA and MCS relationship – A reflection on literature

Although BDA research has grown rapidly, it remains in its early stages, and many key questions remain unanswered (Sheng et al., 2019), particularly regarding its potential to enhance the management accounting function. The image of BDA as a revolutionary tool that can positively impact MCS (Vasarhelyi, Kogan and Tuttle, 2015; Warren, Moffitt and Byrnes, 2015) through prediction and prescription comes with several challenges. Based on a wide-ranging structured literature review, the study identified four broad themes and a supporting theme that illustrates how different forms of BDA impact MCS. Although the body of literature is expanding, there remains a notable conceptual ambiguity regarding the precise mechanisms by which diverse BDA techniques differentially influence the various elements of a MCS. This gap may be expected given the ever-changing nature of BDA techniques, but their role in MCS remains important for the future of management accounting. A key finding of the review was the generation of a clear set of research directions that match different forms of BDA to various aspects of MCS. This template (Figure 20) provides a foundation for this study and enables future research to focus more clearly on gaps in the current literature, so that organisations can realise the undoubted benefits of BDA for MCS.

The review highlights the fragmented yet progressive nature of research on applying BDA to facilitate MCS. These themes are explored in the next section to understand the influence of BDA on the design and use of MCS. Thus, generating a set of potential research areas at the intersection of MCS and BDA, and developing a roadmap for future research in this area (Chapter 8).

Chapter 8 Contributions and Recommendations

8.1 Introduction

The research question that guided this study was:

How do agri-food organisational actors interpret external pressures when using Big Data-enabled control systems, and how does this shape whether control practices are reinforced or changed: A strong structuration theory approach?

To answer this question, I aimed to expand the current body of knowledge by deepening our understanding of how BDA technologies support MCS in the agri-food and beverage industry through analysis of the interview data. This outcome is presented in Chapters 6 and 7 (Findings and Discussion). In addition to the above findings, this chapter presents significant and unique contributions to the knowledge base.

The findings from this study have led to the development of a framework for industry competitiveness, presented in Figure 25, below:

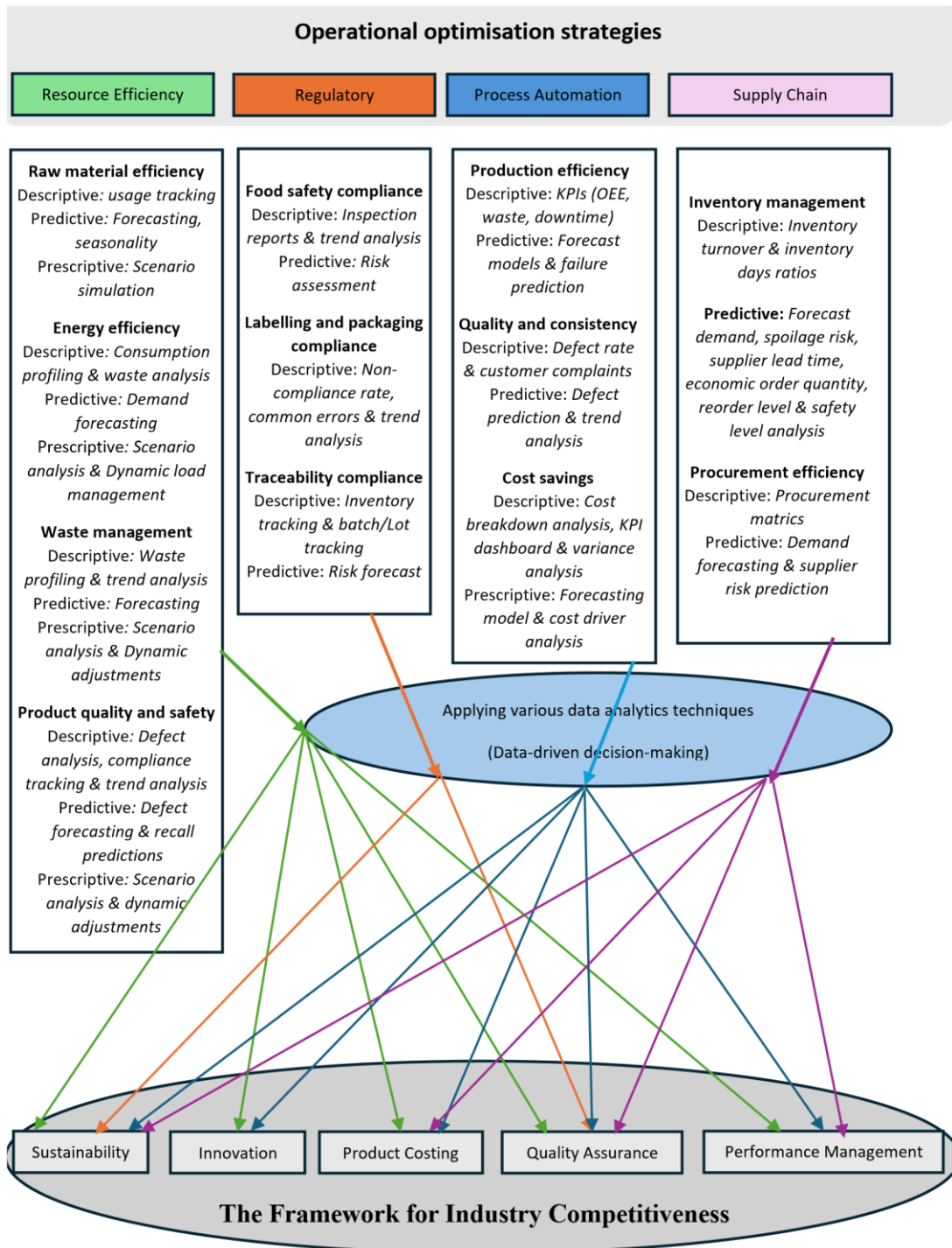


Figure 25: The framework for industry competitiveness

This framework is a strategic blueprint for using data analytics to drive operational excellence and industry competitiveness. It connects granular process improvements to high-level business outcomes, making it a powerful tool for decision-makers in the agri-food and beverage manufacturing industry and other compliance-heavy industries. The framework maps out how different operational strategies, enhanced by

data analytics, contribute to a company's competitive edge. It is structured around four key operational domains (each supported by descriptive, predictive, and prescriptive analytics) that feed into broader industry goals.

The chapter explores the impacts and contributions of this work across various levels. As this study comes to a close, some issues arising from it are now discussed. This begins with the theoretical contributions in Section 8.2, followed by practical contributions in Section 8.3. As with every research project, there are limitations, and explanations of how they were addressed are presented in Section 8.4. Finally, pathways for further research are suggested in Section 8.5, followed by some concluding comments in Section 8.6.

8.2 Theoretical contributions

The literature indicates that a MCS has a much broader scope than traditional management accounting functions (Chenhall, 2003; Haiza Muhammad Zawawi and Hoque, 2010; Bellisario, Appolloni and Ranalli, 2015; Johnstone, 2018; Akinola and Okundalaiye, 2022; Omar *et al.*, 2023; Walambuka, 2024), as organisations operate in an environment of considerable uncertainty (Otley, 2016; Weber, Pedell and Rötzel, 2024). Additionally, there is increasing interest in considering the nature of MCS and organisations' operational strategies, for which ICT tools provide information to maximise system efficiency (Guruswamy *et al.*, 2022; Tavares, Azevedo and Marques, 2022; Habib *et al.*, 2024; Victor *et al.*, 2024). Given the trends in data growth, it has become imperative for businesses to develop the capability to extract information from diverse data sources to support decision-making and other organisational functions. The theoretical contributions presented in this section are based on the secondary research questions: *“How do industry-level analytical developments constitute external structural conditions that shape the use of management control practices in the agri-food and beverage industry?”* and *“How does the agency of management accountants contribute to the reproduction or transformation of control logics and data-driven decision-making practices over time?”* Both questions concern how data are mobilised to design and enact MCS, and how management accountants, as key agents, mediate the relationship between BDA capabilities and organisational control.

The overview of prior studies shows that the vast majority focus on exploring BDA in relation to each MCS component (B. Wang *et al.*, 2019; Duan, Edwards and Dwivedi, 2019; Ciampi *et al.*, 2021; Wang *et al.*, 2022; Singh Bawa, 2023; Tsaniyah *et al.*, 2025). In contrast, this study examines the factors that influence the use of BDA to facilitate MCS, with the aim of achieving the desired outcomes for the agri-food and beverage company. The holistic approach is inspired by the fact that these components (BDA and MCS) do not operate in isolation. Multiple factors contribute to the successful application of BDA to facilitate MCS in the agri-food and beverage industry. These factors may be external to the organisation or internal rules and strategies that managers must follow to ensure that resources are obtained and used effectively and efficiently to accomplish the organisation's objectives. This holistic approach yields a diverse and intriguing set of empirical findings that make significant contributions to the development of the literature in these underexplored areas. This section highlights specific findings on the factors that determine the effective use of BDA to ensure an effective MCS, which have not been previously captured in the literature, thereby making a vital contribution.

External environmental factors significantly shape MCS in the agri-food and beverage industry (Tessier and Otley, 2012; Ferry and McMaster, 2018; Hao, 2024). This thesis uses SST to show how BDA operates as an internal and external structure that enables and constrains MCS, helping agents-in-focus and agents-in-situ reproduce or transform MCS. So, external structures such as regulatory and traceability requirements have led agents to develop the internal structure of BDA to address them. The findings indicate a reciprocal relationship: BDA, having been shaped, then acted as an external structural force that modified the MCS. For organisations to attain these and other strategic objectives, they need to differentiate between the "independent causal influences" that affect the agent-in-focus and the "irresistible causal forces" that the agent-in-focus can work with and resist (Stones, 2005). Agents in the agri-food and beverage manufacturing industry depend on their general knowledge of BDA technologies and on situation-specific knowledge, usually defined by the organisation's MCS. In this regard, individuals or groups in organisations that use

BDA employ organisation-provided resources and their BDA and MCS knowledge, including transferable skills. For example, the financial controller possesses the authority to reconstruct and modify the MCS by integrating functions that utilise BDA. In contrast, without explicit authorisation from the financial controller, a management accountant is restricted to replicating or reinforcing pre-existing functions within the system. This finding contributes to a more nuanced view of how external and internal structures are formed within SST.

BDA is a mechanism that helps organisational members navigate between technical data and control mechanisms. Hence, BDA can help organisations enhance their capability to extract information from various data sources for decision-making (Tsaniyah *et al.*, 2025) and other organisational functions, thereby aligning with their strategies (B. Wang *et al.*, 2019; Wang *et al.*, 2022). The findings in this thesis highlight a transition from traditional, static reporting methods to interactive, real-time dashboards that facilitate decision-making and proactive management rather than serving solely evaluative purposes. Predictive analytics, for example, enables more forward-looking decision-making by leveraging data from IoT sensors to generate more accurate, nuanced predictions (Vudugula *et al.*, 2023; Habib *et al.*, 2024; Ahirrao *et al.*, 2025). This focus on BDA illustrates the tension between technical data and control mechanisms with the MCS framework and sheds light on how levers of control are operationalised. Levers of control, as defined by Simons (1995), have been plagued by measurement issues, operate through managerial subjectivity, and are bounded by organisational culture. This thesis introduces BDA and proposes that it can help reduce measurement issues and minimise subjectivity within the bounds of managerial culture. BDA within MCS can make levers of control more manageable, thereby contributing to the literature.

As outlined in Section 7.4.3, power dynamics significantly influence the agent's capacity to adapt to new technology. By applying the SST framework in this study, a bidirectional relationship is established between external and internal structures, and between agents' use of context and their conduct in producing outcomes. This thesis highlights power differences between the agents-in-focus and those in situ, demonstrating distinct position-practice relationships within their organisation.

Financial controllers act as “agents-in-focus,” shaping strategic investments in analytics IT integration, while IT managers maintain and translate data infrastructures. The management accountant’s position can be understood as either an “agent-in-focus” or an “agent-in-situ,” depending on how they are situated within the organisation’s power relations. For example, a management accountant views the introduction of new BDA dashboards as a chance to shift from a narrow, diagnostic focus on cost control toward a more interactive and forward-looking approach to performance management. This reinterpretation may prompt adjustments to budgeting practices, KPI design, and reporting and managerial dialogue routines. These interactions expose an uneven distribution of power and expertise, affecting how data is interpreted and operationalised within MCS. This contributes to our understanding of how SST can be used to understand the effects of new technologies on positionpractice relationships with organisations.

The empirical findings and the framework (Figure 20) connect BDA techniques directly to operational optimisation strategies, including sustainability, innovation, product costing, quality assurance, performance management, and supply chain management. By integrating analytics across control domains, the study proposes a comprehensive, data-driven MCS that aligns operational execution with strategic goals (Ylijoki and Oy, 2019; Jones *et al.*, 2025; Zahrani and Mukhtaruddin, 2025), while accounting for regulatory and competitive constraints in the agri-food sector. The study therefore recommends using BDA to address challenges in MCS implementation by improving operational control, enhancing resource allocation, and reducing value-chain inefficiencies. Linking MCS to specific operational areas holds great promise for organisations. In particular, the sustainability imperative faced by many industries, especially the agri-food and beverage sector, requires strategic measurement (Maughan and O’Dochartaigh, 2023). There is a lack of this approach in the literature, and this thesis helps fill this gap, particularly given the rise in sustainability reporting requirements.

The research identified other challenges (such as skill shortages, cost barriers, definitional ambiguity, and technological fragmentation) that hinder BDA adoption and integration into MCS. The limited availability of skilled professionals in domains such as data science, machine learning, and BDA generates significant constraints in

data processing, analysis, and interpretation (Didas, 2023; Cassaro *et al.*, 2025). This shortage impedes the industry's ability to effectively leverage data-driven insights for improving operational efficiency, product quality, and innovation, while also hindering compliance with regulatory standards. Meanwhile, as the costs of IT investment increase, IT investment decisions and their alignment with strategic priorities become key areas of decision-making for IT governance (Mangalaraj, Singh and Taneja, 2014; Al-Fatlawi, Farttoosi and Almagtome, 2021). Furthermore, the ambiguity surrounding the term 'big data' poses a significant challenge (Korherr and Kanbach, 2023), as its relative novelty often leaves managers with an incomplete understanding of the diverse data sources available in their industries. These issues can be alleviated through targeted training, IT governance reforms, and managerial advocacy, paving the way for the institutionalisation of analytics-based control. There is a gap in the literature regarding the challenges and potential solutions for integrating BDA into MCS coherently, and the findings of this thesis help address this call for research.

8.3 Practical Contributions

Consistent with Rikhardsson and Yigitbasioglu, the findings indicate that analytics predominantly reinforce diagnostic control mechanisms, especially in contexts characterised by strong compliance demands. By applying SST, however, this study advances prior research by showing that managers' interpretations of external structures shape whether BDA is deployed to stabilise existing control routines or to support their modification and change. Companies in the agri-food and beverage industry face numerous challenges in staying competitive. These challenges include complying with regulations, meeting customer expectations, operating efficiently to ensure profitability, and maintaining quality. This study shows that most of these challenges can be mitigated by using BDA technologies. The contributions in this section directly stem from the secondary research questions: *“How do organisational actors draw upon Big Data Analytics within their internal structures when implementing management control practices?”* and *“How do organisations' position–practice relations enable or constrain the use of BDA-enabled MCS?”*. These questions seek to explain the role of those charged with using BDA to facilitate MCS, and the influence of organisational strategies on the success or failure of the relationship between BDA and MCS.

BDA technologies can help agri-food and beverage manufacturing companies enhance compliance and sustainability through traceability. The ongoing demand and customers' willingness to pay for high-quality products are encouraging agri-food and beverage producers to adopt strict traceability policies. Traceability is also a vital requirement by the FSAI. When combined, prescriptive and descriptive analytics can improve traceability by synthesising historical and real-time data to produce actionable recommendations and insights on best practices within the supply chain. Key variables, such as production location, conditions, and logistics, can be monitored and controlled with a reasonable degree of accuracy. Using these analytics, management can take targeted actions to oversee inventory throughout the production process, from raw materials to finished products. This enables precise tracking from source to destination, leading to greater efficiency and better supply chain management. Accurate material tracking also contributes to more precise labelling, which can be further automated through predictive analytics. Moreover, accurate monitoring of raw materials used in production results in more precise product costs and, consequently, more accurate selling prices. Optimising the supply chain also inherently improves sustainability, as raw materials are sourced from more reliable nearby suppliers, thereby reducing their global carbon footprint.

Effective decision-making relies on the timely availability of relevant information, which can be accessed through BDA technologies. In the agri-food and beverage manufacturing sector, the increasing sophistication of real-time data processing enhances data-driven decision-making. This shift allows the industry to move from intuition-based guesses to precise, evidence-based strategies. For instance, management can respond swiftly to issues on the production line, shifts in market demand, and supply chain disruptions, thereby enabling innovative and dynamic management practices. Predictive analytics can forecast sales figures, weather patterns, social media trends, local events, and even macroeconomic indicators, resulting in much higher demand-prediction accuracy. Deciding how much to produce or order helps optimise inventory levels and reduces both overstock and stockouts, directly decreasing food waste. Similarly, mining data from social media, recipe websites, search trends, and customer reviews enables companies to identify emerging flavours and dietary preferences, guiding decisions on new product development or modifications to existing products. Additionally, predictive analytics improve

companies' ability to segment customers into precise groups for personalised, targeted marketing campaigns. Lastly, sensors on production-line equipment can forecast when a machine is likely to fail, helping management schedule maintenance during planned downtime rather than face a catastrophic failure that halts production.

Diagnostic analytics enable management to investigate the reasons behind every deviation from expected standards (variances). The results of such a diagnosis help align operational metrics with strategic goals, improving performance monitoring. Similarly, BDA technologies could offer new ways to assess employee or process performance using data-driven KPIs. For example, management may be evaluated on how promptly customer complaints are resolved, rather than on the reduction in the number of complaints. A reduction might be caused by customers not bothering to complain, while a faster resolution indicates prompt attention to customers. Furthermore, predictive analytics, which utilises simulation and trend analysis, can help identify issues before the product reaches customers. Consequently, agri-food and beverage manufacturers can proactively anticipate and address issues by examining standard parameters, such as temperature, humidity, and ingredient quality.

Overall, using BDA to facilitate MCS can only be beneficial if there is a clear line of communication between the IT department and the production floor or operations. To ensure that data-driven decisions are both well-informed and actionable, they must be grounded in context, operational practicality, and the organisation's performance objectives. Otherwise, important information may be lost, or irrelevant systems may be purchased, leading to unsustainable operations. The IT department is primarily responsible for overseeing technological infrastructure, managing data pipelines, and maintaining analytical systems. In contrast, operational teams on the production floor hold essential domain-specific expertise. As a result, IT personnel may have limited insight into the nuanced, day-to-day dynamics of manufacturing, including identifying critical data points, recognising operational anomalies, and understanding the broader implications of production delays on the supply chain. Conversely, production staff possess intimate knowledge of machinery, process workflows, typical failure modes, and the immediate challenges encountered in real-time operations. Accordingly, they possess the expertise to discern which sensor outputs are operationally relevant and

which are extraneous or non-actionable. Essentially, without a strong link between the IT department and the production floor, the potential benefits of BDA are lost.

The study demonstrates how BDA facilitates monitoring productivity, optimises resource allocation, and reduces waste across the value chain. Managers can use these findings to refine or redesign MCS processes, thereby improving operational efficiency and reducing costs.

8.4 Limitations of the Research

Given the research approach, which considers multiple variables to identify the listed contributions, this study undoubtedly has limitations, including the data collection method, the industry selected, the size of participating companies, and the study timeframe. These limitations and the steps taken to mitigate their impact on the results are explained below.

To arrive at the above contributions, I adopted a rigorous data collection and analysis process to mitigate some of the challenges qualitative researchers face. In general, participants are considered knowledgeable in their industry, and the researcher is also assumed to have prior knowledge of the topic under investigation. Therefore, I avoided imposing prior constructs or theories on the participants, minimising the risk of a priori explanations for understanding or explaining how data is harnessed and used in their manufacturing processes. In this regard, I took a stance of well-intended ignorance, as demonstrated by Gehman et al. (2018). The initial questions were designed to allow participants to speak freely about the manufacturing processes within their organisation, the types of data generated, and how they are used. This approach to questioning gave me two advantages and one main disadvantage. Firstly, the generic nature of the questions posed to all participants, regardless of the products manufactured, meant I did not intend to narrow the responses. This approach allowed me to elicit a significant amount of detail from the participants. Every agri-food and beverage company has different processes depending on the type of product it manufactures. In this regard, every effort was made to select participants from across a diverse range of agri-food and beverage companies, but it was not possible to cover

the full range of different food and beverages, especially in a qualitative study where depth is an important requirement.

However, this study aimed to develop a framework applicable to all agri-food and beverage companies and, in future work, extend it to other process-intensive manufacturing companies. Therefore, the open-ended question approach allows the results of this study to be generalisable. Secondly, by prompting the participants to narrate their processes, I gained information that would have been limited by my knowledge of the organisation. Before starting the interview, I conducted background research on the organisations and sought to thoroughly understand each participating organisation's strategies. In many cases, using publicly available information, it would have been possible to phrase the questions in a very specific manner to confirm or refute how data is used to achieve their strategic objectives. On the other hand, I sensed that some participants were concerned about my knowledge of their organisation, as I was not forthcoming with specific questions about their strategies. These worries were usually cleared with the probing questions that followed. Additionally, at the conclusion of the interviews, I explained why they had taken a stance of well-intended ignorance, and the participants were usually pleased to learn of this approach. The richness of the outcomes from this research testifies to the importance of minimising the impact of my positionality on data collection.

Besides the usual limitations of collecting data via interviews, the inability to conduct face-to-face interviews added an extra layer of challenges. The interviews were conducted on Teams, in line with post-COVID norms, and captured a wide geographic spread of participants. Although this approach is often regarded as more cost-effective, faster, safer, and more scalable, it nonetheless presents several limitations. The most prominent limitation in this study is the omission of non-verbal cues, such as body language, facial expressions, or physical context. The limitations of body language and facial expressions were reduced because the interviews were video-recorded, and I always probed further when needed. The study would have benefited most if the interviews had been conducted in the factory, where I could have accessed the production lines and observed the IoT in operation. which can reduce the nuance in interpreting emotions or emphasis. This limitation was mitigated by building rapport

up front with warm-ups and follow-up questions, and triangulating with documents obtained from the company's website.

As mentioned earlier, BDA is especially critical in the agri-food and beverage manufacturing industry because it directly affects food safety, compliance, and consumer demand. Other industries also benefit from BDA, but the agri-food and beverage industry is unique in that it is regulated, handles perishable products, is sensitive to consumer demand, and has complex operations (automated processes and supply chain systems). These factors make real-time, predictive, and prescriptive analytics not just beneficial but essential in the agri-food and beverage industry. Other industries that would have been good choices for this study include the pharmaceutical and medical device industries. The pharmaceutical industry shares characteristics with the agri-food and beverage industries, except that its products are non-perishable. Similarly, the medical devices industry is regulated, quality-sensitive, compliance-heavy, and involves complex manufacturing processes, but it neither handles perishable products to the same extent nor responds to extreme fluctuations in consumer demand to the same extent. Hence, the agri-food and beverage industry was considered most appropriate for this study. The focus on the agri-food and beverage industry could overlook standard features of all process-intensive, highly regulated industries.

This study was conducted in Ireland, where the FSA strictly enforces food regulations and the Irish population is highly health-conscious about their eating habits. Ireland was considered an ideal location for the study for the above reasons, in addition to the ease in collecting qualitative data through interviews with local companies. If this study were conducted in a different country with the same parameters, the results could differ or confirm. This limitation reduces the generalisability of the results of this study to countries with regulatory requirements similar to those in Ireland.

Similarly, the study was conducted within the timeframe permitted for PhD studies, and the research must respect that timeframe. If this study were conducted over a longer period, it would allow for greater flexibility in expanding data collection. A longitudinal study of a single company fully immersed in the use of BDA to facilitate

MCS might reveal further nuances in this relationship. This study approach will be more relevant if the company changes or upgrades its system during the study period.

Advances in cognitive analytics and AI have led to a move towards robotic manufacturing processes powered by cognitive decision-making algorithms, ambient intelligence tools, and distributed sensor networks (Lăzăroiu *et al.*, 2022; Nuankaew, Nasa-Ngium and Nuankaew, 2025). Industry 6.0 is tipped to be making its way into manufacturing as the conceptual successor to Industry 5.0, and is projected to be defined by widespread AI-driven automation, the utilisation of quantum computing, and advanced levels of human-machine symbiosis (Duggal *et al.*, 2022; Maljugić *et al.*, 2024; Gomaa, 2025). At the time of data collection for this study, cognitive analytics, artificial intelligence, and the principles of Industry 5.0 were still emerging and had not yet been widely implemented. Consequently, these advanced technologies were not incorporated into the research. However, their growing relevance and potential influence on MCS are increasingly significant and warrant future consideration.

Geminarqi and Purnomo (2023) recommend that a researcher should conduct a hands-on investigation into the effective use of data analytics technologies, as this provides practical insights, validates theoretical models, and enhances the relevance and impact of the research. Hands-on investigation allows researchers to test how data analytics tools perform in actual industrial settings, thereby confirming whether theoretical benefits, such as improved efficiency or decision-making, hold up under operational conditions. In this study, data were collected through interviews, a method with limitations. Thus, care was taken to ensure only knowledgeable personnel were considered for the interviews. The financial controller, management accountant and the IT manager are expected to be grounded in the organisation's MCS and its information requirements. Therefore, it is believed that the results of this study reflected the BDA-MCS relationship, but a data collection approach that involved the researcher gaining access to the system and performing the review themselves may reveal nuances not captured by interviews. In addition, when interviewing even the most knowledgeable people in the organisation, there is a risk associated with self-reported data. Self-reported data can be subject to biases like social desirability bias, recall bias, or misinterpretation of questions. I used triangulation to corroborate

self-reported data with information from the participants' strategic declarations extracted from their websites. The study also included consulting with an independent expert to validate responses. The independent expert is a software provider that specialises in delivering software and related services to agri-food and beverage companies. Their input corroborates the assertion that BDA facilitates MCS in the industry.

8.5 Recommendations for Future Research

Although BDA research has grown rapidly, it remains in its early stages, with many crucial concerns unaddressed, particularly regarding how it may benefit the management accounting function. A key discovery of this research is the establishment of a distinct array of research trajectories, aligning various kinds of BDA with different components of MCS. This template contains questions that will enable future research to focus more clearly on gaps in the current literature so that organisations can realise the undoubted benefits of BDA for MCS (Appendix H).

As discussed in section 7.3, this study and the academic literature suggest that resource efficiency, regulatory compliance, process automation, and supply chain management are operational optimisation measures. Food manufacturers must maximise output, minimise resource waste, and reduce expenses to boost production efficiency. Omar et al. (2019) suggest that it is logical for the manufacturing industry to focus on optimising input resources to identify opportunities to reduce raw material, water, and energy costs, eliminate waste, and improve efficiency, yield, and conformance with sustainable practices. These tasks can be facilitated using BDA, as explained in section 7.3. This study has developed a framework to guide managers in the agri-food and beverage industry in maximising the use of BDA technology. It demonstrates the approach to using BDA to facilitate MCS; however, these principles require further testing. The study did not confirm how many similar companies are using the technologies. In this regard, empirical investigations using statistical methods, such as cluster analysis, could be conducted to determine the extent to which BDA is utilised to facilitate MCS. Such a study should dive deeper into the factors that influence the use of BDA to facilitate MCS.

In section 7.4, this study contextualises MCS by using SST to understand agentic concerns in adopting BDA in agri-food and beverage companies. The objective is to differentiate between the "independent causal influences" that affect the agent-in-focus and the "irresistible causal forces" that the agent-in-focus may be able to work with and resist. Using SST as the theoretical lens helps explain how the agency reproduces or changes the BDA-MCS environment in food processing. This study utilises SST to demonstrate that technology can facilitate MCS, but MCS structures also define the organisation's technological needs. Individuals or groups in organisations that use BDA employ organisation-provided resources and their BDA and MCS knowledge (including transferable skills). The financial controller can recreate and change the MCS structure by adding BDA-using functions. Without the financial controller's approval, a management accountant can reproduce or reinforce existing functions. Besides other restrictions, the organisational structure that defines essential duties determines the potential of the BDA-MCS relationship. It is therefore necessary to investigate how organisational structure influences the use of BDA to facilitate MCS. This advanced knowledge can be achieved by focusing on a single case study that has fully adopted big data technologies. Such studies will uncover a more comprehensive framework for using BDA to facilitate MCS. As explained in Section 6.2, the successful implementation of the various MCS components identified in this study depends on multiple factors identified through the SST analysis (Appendix F – SST intersection with MCS themes). The study highlights the importance and ability of humans to apply technologies to resolve issues.

Sustainability and innovation are two crucial principles in the modern agri-food and beverage industry (Maughan and O'Dochartaigh, 2023), and Industry 4.0 has been at the forefront of advancing these principles (Gomaa, 2025). As highlighted in section 7.4.4, digitalisation and intelligent manufacturing are elevating the food production industry to unprecedented levels of efficiency. Integrating IoT, AI, and BDA (Industry 4.0) into manufacturing processes creates "smart factories" that enhance production efficiency in real-time. This optimisation ensures the most effective utilisation of resources and sustains efficiency in the supply chain management system, enabling more precise forecasting of customer demand and thereby minimising overproduction and waste. Building on the achievements of Industry 4.0, Industry 5.0 is the next phase

in industrial evolution (Raja Santhi and Muthuswamy, 2023). While Industry 4.0 focuses on automation, innovative technology, and data-driven processes (e.g., IoT, AI, robotics), Industry 5.0 prioritises human-centricity, sustainability, and human-machine collaboration. The principal effect of Industry 5.0 is the equilibrium between automated efficiency and human creativity, resulting in more personalised and sustainable production techniques (Maljugić *et al.*, 2024). This evolution will likely reshape manufacturing processes to incorporate humans, thereby redefining the agentic involvement in using BDA to facilitate MCS, and it warrants a thorough investigation. It is therefore essential to use SST to appreciate the agentic challenges that arise, as well as BDA, in agri-food and beverage manufacturing companies.

While food safety is the most important aspect of the agri-food and beverage industry, it is crucial to have a robust data architecture in place to enable effective use of predictive analytics for HACCP evaluation. Food companies operating in every member state are required by EU laws to apply a food safety management system grounded on HACCP guidelines. Hazard analysis is best implemented proactively to avoid the consequences of food safety failures. Therefore, food manufacturers will increasingly implement predictive analytics. It is essential to remember that the predictive analytics methods employed will vary according to the unique requirements and resources of agri-food and beverage companies. In this regard, it is necessary to develop a framework that maximises the use of predictive analytics in implementing food safety management systems, such as HACCP. An exhaustive analysis of a food factory that employs predictive or advanced data analytics to implement HACCP can be conducted.

Furthermore, this study explored the holistic use of BDA to facilitate MCS and to help food manufacturers understand and explain this under-researched area. This holistic process is multi-faceted, and future research could concentrate on studying any one aspect of this process in more detail, for example:

- How can BDA foster resource efficiency, regulatory compliance, process automation, and supply chain management to attain sustainability?
- How does innovation benefit from employing BDA to maximise resource efficiency and process automation?

- Does the enhancement of resource efficiency, process automation, and efficient supply chain management affect product costing? A cost-benefit analysis.
- Quality assurance is one of the most critical aspects of food manufacturing, as it ensures compliance with regulatory requirements. Inefficient resource management, inadequate process automation, and poorly designed supply chain management systems can adversely affect this objective. Can BDA make these tasks any easier?
- Performance management is the cornerstone of every business, and it has been researched extensively; however, not from the perspective of using BDA to facilitate operational optimisation strategies in the agri-food and beverage industry, as outlined in the framework (Figure 20).

In conclusion, acknowledging the limitations inherent in this study, several corrective measures have been proposed to mitigate their impact. These limitations create research opportunities in the field, as seen from this study (da Silva *et al.*, 2023). Acting on these opportunities not only strengthens the current research but also opens up potential directions for future investigations to advance understanding in this field. Examples of such measures include:

- Carrying on the research in a different industry, which shares many characteristics with the agri-food and beverage industry. For example, a similar study could be conducted in the pharmaceutical or medical devices industry, and the results could be compared and contrasted to identify a pattern that applies across all process-intensive, highly regulated industries.
- Carrying on the research in a different country which shares similar characteristics with the Irish agri-food and beverage industry. For example, a comparative study may be conducted in the United States of America or another EU member state to reveal similarities or differences.
- A longitudinal study of a single company fully immersed in using BDA to facilitate MCS might reveal more nuances in this relationship. This study approach will be more relevant if the company changes or upgrades its system during the study period.

- A similar study may focus on AI and cognitive analytics to examine how these and advanced analytics impact MCS, especially as manufacturing moves to Industry 6.0, reintegrating humans into automating manufacturing processes (Maljugić *et al.*, 2024).
- A data collection approach may involve the researcher gaining access to the system and performing the review themselves. This approach may reveal more nuance than can be obtained from interviews.

Overall, many aspects of using BDA to facilitate MCS warrant exploration in future studies; the overview above serves as a starting point. Similar studies could also be conducted in other process-intensive industries that generate unstructured, complex real-time data, which can be used to gain or maintain a competitive advantage.

8.6 Concluding Remarks

This thesis has explored the intersection of BDA and MCS within the agri-food and beverage industry, offering both theoretical and practical insights into how data-driven technologies are reshaping organisational control and decision-making. Through a qualitative research design grounded in SST, the study examined the lived experiences and perspectives of financial controllers, management accountants, and IT managers, providing a rich understanding of how BDA is operationalised within complex organisational contexts. The findings emphasise the transformative potential of BDA in enabling more responsive and strategically aligned MCS.

This study highlights the importance of organisations developing the capability to extract information from diverse data sources to support decision-making and other organisational functions. BDA helps organisations stay aligned with their strategies, thereby maximising the likelihood of achieving their primary objectives. The study provides a detailed examination of the quadripartite structure of SST and its alignment with the situational context and behavioural practices of individuals tasked with employing BDA to enhance MCS. Thus, SST emphasises the vital roles and responsibilities of managers involved in the manufacturing process. The study advances the quadripartite nature of SST by conceptualising it as a multidirectional analytical framework (the Reverse Funnel model) suitable for examining research scenarios characterised by multiple mediating factors.

The practical contributions of this study emphasise strategic recommendations that demonstrate how adopting BDA technologies can alleviate the challenges associated with implementing MCS. For example, BDA technologies can help agri-food and beverage manufacturing companies enhance compliance and sustainability by enabling traceability, supporting effective decision-making, and accurately tracking variances. The study also finds that using BDA to facilitate MCS is beneficial only if there is a clear line of communication between the IT department and the production floor or operations. The study illustrates the role of BDA in enhancing operational control by enabling precise monitoring of productivity levels, improving strategic resource allocation, and minimising inefficiencies throughout the value chain.

Alongside the practical and theoretical contributions, the thesis filled a significant gap in the existing literature by synthesising research on BDA and MCS. The review revealed a lack of integrated studies exploring how data analytics and control systems co-evolve, particularly in the agri-food and beverage industries. By addressing this gap, the study enhances understanding of how digital technologies are incorporated into organisational routines and strategic frameworks.

Overall, this research confirms that the effective deployment of BDA is not just a technical task but a deeply contextual and strategic process. It urges a rethinking of traditional control paradigms to accommodate the dynamic, data-rich environments in which modern agri-food and beverage organisations operate. Future research may build on these findings by examining the long-term impacts of BDA on organisational learning, cultural change, and cross-functional collaboration, further enhancing the discourse on digital transformation and control in complex industries.

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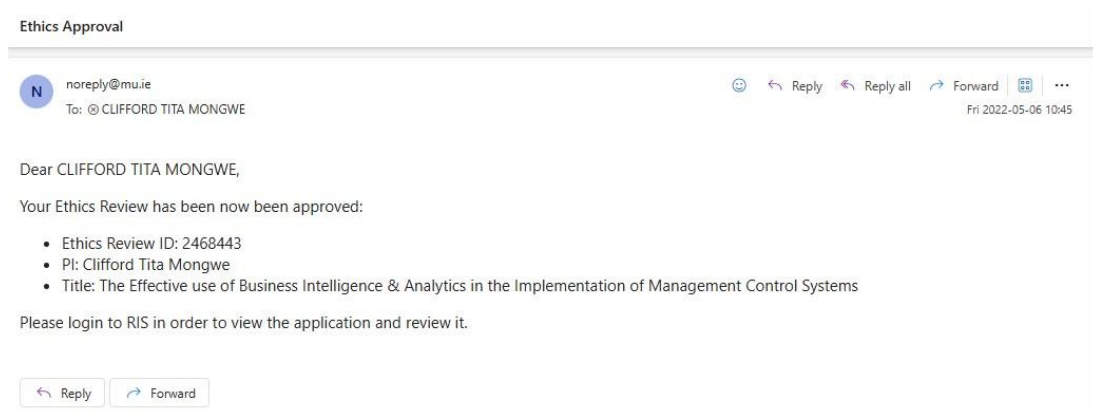
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Appendices

Appendix A – Ethical Approval

A screenshot of the ethical approval for this study by Maynooth University's Social Research Ethics Sub-Committee.



Appendix B– Participant's Information Sheet



Request to participate in a research study for the completion of a PhD thesis

Purpose of the Study

The study is concerned with the effective use of big data analytics in the design and use of management control systems. Specifically, I am investigating how big data facilitates management control functions within the agri-food and beverage industry.

What will the study involve?

The study will involve the participation of managers who implement big data technologies in their organisations. It will consist of a series of interviews. Lines of inquiry will include the nature of the business processes (strategies) that may use big data, the procedure to capture, record and analyse data to evaluate the success of each process, participants' perception of what makes big data implementation successful, and challenges encountered.

Who has approved this study?

This study has been reviewed and received ethical approval from the Maynooth University Research Ethics Committee. You may have a copy of this approval if you so wish.

Why have you been asked to take part?

Your organisation has achieved exceptional levels of quality recognised locally and internationally. We invite you to participate in this study because it focuses specifically on the agri-food and beverage industry rather than general manufacturing. This study will greatly benefit from your input if you actively use one of the recognised big data systems. Examples of big data systems include Microsoft BI/Dynamics/Azure, Oracle NetSuite, SAP, Google Analytics, Sisense, DIOMAC, Herbst, etc.

Do you have to take part?

No, you are under no obligation whatsoever to participate in this research. It is entirely up to you to decide whether or not you would like to participate. However, we hope you will agree to take part and give us some of your time to participate in an interview with the researcher.

If you choose to participate, you are free to withdraw without providing a reason and/or withdrawing your information until the research findings are published and the final thesis is submitted upon the study's completion. If you decide to do so, you will be asked to sign a consent form and be given a copy of the information sheet for your records. A decision to withdraw at any time or not to participate will not affect your relationships with Maynooth University.

What information will be collected?

Data will be collected through interviews with research participants, which will be recorded with the informed consent of the participants before being transcribed and analysed. The types of information that will be sought after by the researcher will include anecdotal evidence of the use of big data analytics to assist in implementing business processes and participants' personal experiences and opinions on the usefulness and challenges of big data analytics implementation.

Secondary data may be collected by reading and analysing information on the company's website and/or documents the firm may provide to the researcher regarding its business processes, software packages, etc. Such information received the same security and anonymity as the interview data.

Will your participation in the study be kept confidential?

All information collected about you and your organisation will be confidential during the research. The identity of the organisations taking part will also be anonymised. The only descriptive information disclosed is that they will be F&B companies and use big data technologies for their day-to-day operations. No names will be identified at any time.

All hard-copy information will be kept in a locked cabinet at the researchers' place of work (School of Business, Maynooth University). Electronic information will be encrypted and stored securely on a MU PC or server. It will be accessed only by the researcher, Clifford Mongwe, and the research supervisors, Prof Joseph Coughlan and Dr Bridget McNally.

No information will be distributed to any other unauthorised individual or third party. If you wish, the data you provide can also be available at your discretion.

Please also note the following:

It must be recognised that, in some circumstances, the confidentiality of research data and records may be overridden by courts in case of litigation or investigation by lawful authority. In such circumstances, the University will take all reasonable steps within the law to ensure confidentiality is maintained to the greatest extent possible.

What will happen to the information which you give?

All the information you provide will be securely stored at Maynooth University, so identifying you is impossible. Upon completion of the research, the data will be retained on the MU server for ten years, after which all data will be destroyed. Manual data will be shredded confidentially, and electronic data will be erased using a digital file shredder, reformatted or overwritten 3-5 times.

What will happen to the results?

The research will be written and presented as a final thesis for submission for consideration for a PhD. Further outputs may include individual papers for submission to academic conferences, peer-reviewed journals, and/or industry publications. A copy of the research findings will be available upon request.

What are the possible disadvantages of taking part?

I don't envisage any negative consequences for you in participating, but I am available to discuss any potential concerns you may have regarding participation.

What if there is a problem?

At the end of the interview, you can elaborate on how you found the experience and how you feel. You may contact my research supervisor, Prof Joseph Coughlan, by email (Joseph.Coughlan@mu.ie) or phone (01 474 7560) if you feel the research has yet to be carried out as described above.

Any further queries?

If you need further information, please get in touch with me by email: clifford.mongwe@mu.ie.

Thank you for taking the time to read this and for considering participating in this study.

Appendix C – Consent Form for Participants



Consent Form

I.....agree to participate in Clifford Mongwe’s research study titled “The Effective use of Business Intelligence & Analytics in the Implementation of Management Control Systems”.

Please tick each statement below:

The purpose and nature of the study have been explained to me verbally & in writing. I’ve been able to ask questions, which were answered satisfactorily. ☐ I am participating voluntarily. ☐

I permit my interview with Clifford Mongwe to be recorded ☐

(Note: Teams application records both aurally and visually)

I understand that I can withdraw from the study, without repercussions, at any time, whether that is before it starts or while I am participating. ☐

I understand that I can withdraw permission to use the data right up to the submission of the thesis [circa] ☐

It has been explained to me how my data will be managed and that I may access it on request. ☐

I understand the limits of confidentiality as described in the information sheet ☐

I understand that my data, in an anonymous format, may be used in further research projects and any subsequent publications if I give permission below: ☐

[Select as appropriate]

I agree to quotation/publication of extracts from my interview ☐

I do not agree to quotation/publication of extracts from my interview ☐

I agree that my data be used for further research projects ☐

I can't entirely agree for my data to be used for further research projects ☐

I agree for my data, once anonymised, to be retained indefinitely in the IQDA* archive ☐

I can't entirely agree for my data, once anonymised, to be retained indefinitely in the IQDA archive ☐

☐

Signed.....

Date.....

**The Irish Qualitative Data Archive (IQDA) is a central access point for qualitative social science data generated in or about Ireland. The archive frames the parameters and standards for archiving qualitative data within the Irish research community*

Participant Name in block capitals

I, the undersigned, have taken the time to fully explain to the above participant the nature and purpose of this study so they could understand. I have explained the risks involved as well as the possible benefits. I have invited them to ask questions on any aspect of the study that concerned them.

Signed.....

Date...27/06/2022.....

Researcher Name in block capitals ...CLIFFORD MONGWE.....

If during your participation in this study, you feel the information and guidelines that you were given have been neglected or disregarded in any way, or if you are unhappy about the process, don't hesitate to get in touch with the Secretary of the Maynooth University Ethics Committee at research.ethics@mu.ie or +353 (0)1 708 6019. Please be assured that your concerns will be dealt with sensitively.

The Data Controller for this research project is Maynooth University, Maynooth, Co. Kildare. Maynooth University Data Protection Officer is Ann McKeon in Humanity house, room 17, who can be contacted at dataprotection@mu.ie. Maynooth University Data Privacy policies can be found at <https://www.maynoothuniversity.ie/data-protection>.

Two copies to be made: 1 for the participant, 1 for PI

Appendix D – Interview Guide

Theme 1: Big data in context (reaffirm the use of big data in the case study organisation)

- Your role and responsibilities
- The accounting software system is used within the firm. Strategic fit/alternatives
- Definition and awareness of what constitutes big data and how it applies to your firm

Theme 2: How does big data analytics affect the core role of management control

- Impact on the efficiency of manufacturing processes
- Other uses of big data in your firm

Theme 3: How does MCS structure influence the need for BDA technologies

Controls to ensure the effectiveness of:

- Core values of the firm (vision and mission statements, organisational structure)
- Risk to be avoided
- Critical performance variable (KPI)
- Strategic uncertainty (Brexit, Covid-19, Russia-Ukraine war etc.).
- Impact on supply chain, labour force, sales etc

Theme 4: Barriers to effective use of BDA in MCS

- Rapid change and resistance to change
- Budgetary constraints – value for money
- Organisational structure (line of communication between IT and other managers)
- Lack of qualified BDA personnel
- Knowledge of the definition of big data
- Regulatory or legal constraints and ethical issues
- Other barriers to using and creating value from big data (organisational, managerial, technical etc.)

Appendix E – Interview Questions

Theme 1: Big data in context (reaffirm the use of big data in the case study organisation)

- *Please talk me through your role and responsibilities at the firm*

- The accounting software system is used within the firm. Strategic fit/alternatives

What is the accounting package currently used to capture and analyse data?

Are you satisfied with its performance? Any alternative you would have wished to use

- Definition and awareness of what constitutes big data and how it applies to your firm:

What is your knowledge of what constitutes big data? Any examples of big data at Keogh's Crisp?

Theme 2: How does big data analytics affect the core role of management control

Impact on the efficiency of manufacturing processes:

- *What types of data do you collect from the factory floor?*
- *What are the key reasons for the need to implement big data analytics*
- *Besides the manufacturing processes, what other ways do you use big data, if any?*

Theme 3: How does MCS structure influence BDA technological needs (Levers of control)

Controls to ensure the effectiveness of:

- Core values of the firm (vision and mission statements, organisational structure) ○ *Are all employees aware of your organisation's core values, like the mission statement? Otherwise, what level of responsibility are they required to be tuned in? How is this monitored (data source) ○ Who authorises the acquisition of new systems?*
- Risk to be avoided ○ *Are there any punitive measures if employees deviate from the core values? Please talk me through some examples, if any.*

- Critical performance variable (KPI) ○ *As a manufacturing firm, what are some of the KPIs that drive your strategies? What data is collected to evaluate them?*
- Strategic uncertainty (Brexit, Covid19, Russia-Ukraine war, etc.) ○ *Do you import any of your raw materials? If so, how has your supply chain been affected by the current turbulences in the world?*
 - *What is the impact on your labour force?* ○ *Any impact on your sales or customers?*
 - *How can data analytics help in these circumstances?*

Theme 4: Barriers to effective use of BDA in MCS

- Rapid change and resistance to change: ***How easy was it to implement the new system or upgrade?***
- Budgetary constraints – value for money: ***Who authorises the purchase or investment in IT systems***
- Organisational structure (line of communication between IT and other managers): ***How efficient is the line of communication between the IT team and the other managers***
- Lack of qualified BDA personnel: ***Do you have enough hands-on deck to deal with data collection, cleaning, warehousing, etc. (ETL process)***
- Resistance to change and change management ***Have you recently upgraded or implemented a new system?***

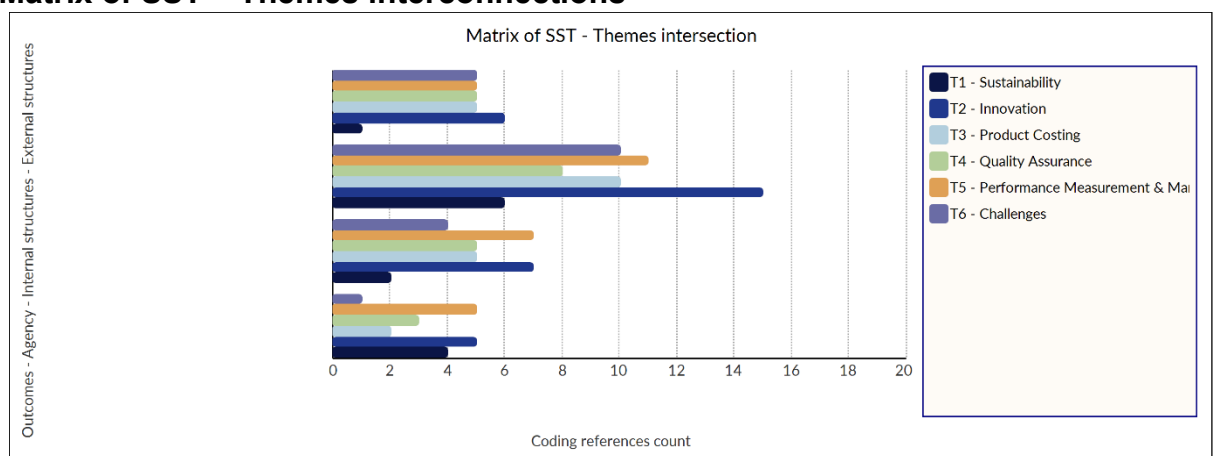
How easy/difficult was it when a new system was introduced?

- Knowledge of the definition of big data: Data source not fully exhausted: ***Do you think you have access to all the data you generate (directly and indirectly)? Which data source may be missing?***

- Regulatory or legal constraints and ethical issues: *Are there any regulatory or legal constraints that may obstruct the collection and use of data within your industry? Any ethical issues?*
- Other barriers to using and creating value from big data (organisational, managerial, technical, etc.): *What, in your opinion, could be other challenges limiting your ability to exhaustively explore the power of big data?*

Appendix F – SST intersection with MCS themes

Matrix of SST – Themes interconnections



A matrix of SST components intersecting with MCS Themes

MCS Themes SST components ↓	T1 - Sustainability	T2 - Innovation	T3 - Product Costing	T4 - Quality Assurance	T5 - Performance Management	T6 - Challenges
External Structures	1	6	5	5	5	5
Internal structures:						
Situational Knowledge	3	4	2	2	4	2
General Dispositions	3	11	8	6	7	8
Agency:						
Agent-in-focus	2	5	4	4	5	3
Agent-in-situ	0	2	1	1	2	1
Outcomes:						
Reproduction	2	3	1	2	3	0
Transformation	2	2	1	1	2	1

Appendix G – NVivo extracts (Themes)

T1 - Sustainability and supporting sub-themes

Name	Files	References
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T1 – SUSTAINABILITY	35	517
<i>Resource Efficiency</i>	24	146
ITGovernance	12	62
Processes	12	38
Value Creation	12	25
Visualisation	9	21
<i>Waste Management and Carbon Footprint Reductions</i>	24	135
Risk Management	10	38
Change Management	14	50
Supply chain	20	47
<i>Transparency and Traceability</i>	32	215
System Quality	20	102
Product Quality	13	31
LOC-Diagnostic	14	35
Supply Chain	20	47

T2 - Innovation and supporting sub-themes

Name	Files	References
T2 - INNOVATION	43	423
<i>Product Innovation</i>	37	128
Value Creation	12	25
LOC-Belief	22	38
LOC-Boundary	19	34
Product Quality	13	31
<i>Process Innovation</i>	28	180
Change Management	14	50
Processes	12	38
Optimisation	18	44
<i>Supply Chain Innovation</i>	23	115
Visualisation	9	21
Supply Chain	20	47

T3 - Product costing and supporting sub-themes

Name	Files	References
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T3 - PRODUCT COSTING	39	602
<i>Total product cost (Direct and OH costs)</i>	27	222
Cost accumulation	16	47
Processes	12	38
System Quality	20	102
LOC-Diagnostic	14	35
<i>Quality Control and Compliance Costs</i>	35	257
LOC-Belief	22	38
Processes	12	38
Supply Chain	20	47
Skills	13	32
System Quality	20	102
<i>Product Development and Cost Management</i>	22	79
Optimisation	18	44
LOC-Diagnostic	14	35

T4 - Quality assurance and supporting sub-themes

Name	File	Referenc
T4 - QUALITY ASSURANCE	38	363
<i>Standard Operating Procedures and Good Manufacturing</i>	36	222
LOC-Belief	22	38
Optimisation	18	44
Risk Management	10	38
System Quality	20	102
<i>Regulation and compliance</i>	26	73
LOC-Diagnostic	14	35
LOC-Belief	22	38
<i>Supply chain management</i>	23	68
Visualisation	9	21
Supply Chain	20	47

T5 - Performance management and supporting sub-themes

Name	Files	References
T5 - PERFORMANCE MEASUREMENT & MANAGEMENT	41	515
<i>Key Performance Indicators (KPIs)</i>	25	306
LOC-Interactive	10	26
Performance metrics	18	48
Value creation	12	25
Visualisation	24	134
<i>Regulation and Compliance</i>	26	73
LOC-Diagnostic	14	35
LOC-Belief	22	38
<i>Benchmarking and Continuous Improvement Processes</i>	29	135
LOC-Diagnostic	14	35
Optimisation	18	44
Product Quality	13	31
Value Creation	12	25

T6 - Challenges and supporting sub-themes

Name	Files	References
T6 – CHALLENGES	35	632
<i>Lack of qualified BDA personnel</i>	20	130
Change Management	14	50
Skills	13	32
<i>Resistance to change and change management</i>	30	172
Change Management	14	50
LOC-Belief	22	38
LOC-Boundary	19	34
<i>Definition and awareness of big data</i>	19	128
Barriers	18	98
Definition	13	30

<i>High Costs, Resource Allocation and Interoperability with IoT Devices</i>	25	202
ITGovernance	12	62
Processes	12	38
System Quality	20	102

Appendix H - Mapping of MCS and BDA themes to potential research areas based on MCS themes

Theme	BDA type	Research context	Potential areas for further research
Planning	Diagnostic	Big data as a facilitator of the budgeting process	What is the role of big data analytics techniques in budgeting?
			How can big data analytics facilitate a more digitalised budgeting process?
	Predictive	Influence of big data on the Design and Use of performance measurement tools	How can big data analytics be used to design new performance management tools?
Decisionmaking	Descriptive	Choosing an appropriate visualisation may increase usability	How do visualisation techniques, such as dashboards, impact decision-making?
	Diagnostic	Does increased availability of data improve decision-making?	What is the role of big data analytics in assisting board-level and C-suite executives in responding to environmental changes while anticipating stakeholder needs rapidly?
			Does BDA improve the quality of decision-making?
			How effectively are BDA technologies automating traditional management accounting functions like monitoring and reporting?
	Prescriptive	Influence of big data on the Design and Use of performance measurement tools	How do BDA-informed decisions differ from those made without the aid of BDA?
Control	Descriptive	Can the availability of more data improve product costing?	How do process-intensive manufacturing companies harness the power of big data analytics to improve their production processes?
			How could BDA be employed to identify more applicable cost drivers?
		Automation may capture data beyond organisations' ability to protect	How do organisational structure and top management commitment influence the adoption of big data analytics?
		Big data may cause a redefinition of accounting concepts and principles	Has the quality of financial statements improved with big data analytics?
			What is the role of big data analytics in fraud detection?
		Advances in data analytics would affect auditing and the audit profession, which is a big data consumer.	How do auditors perceive and utilise big data analytics techniques in their practices? (Gepp et al., 2018).
			Can 100% substantive testing be achieved with the aid of big data? Using statistical procedures and/or machine-learning techniques improves the efficiency of targeted substantive audit tests (Appelbaum <i>et al.</i> , 2017).
	Diagnostic	Diagnostic and predictive BDA significantly impact how organisations can control their operations.	What is the role of customer reviews in setting performance targets?
	Predictive		How do ethical considerations affect BDA implementation?
			Can prescriptive analytics enable decision automation? The challenges of uncertainty, dynamicity, and complexity (Lepenioti et al., 2020).

Theme	BDA type	Research context	Potential areas for further research
Value creation	Predictive	Can big data bring improvements to old accounting techniques?	How does BDA influence a target costing system's successful design and use? How can costing systems become more dynamic and responsive to changes through BDA?
		Curriculum changes to embrace big data in accounting education	How has the integration of BDA within both professional and university accounting curricula changed over the last decade, and what is the impact of this change?
		Do businesses have enough skilled big data professionals? Outlook for preparing future accountants for the use of big data	How has BDA affected the management accountant's role? A skills gap analysis (Brands and Holtzblatt, 2015)
			How do BDA requirements differ by organisation size and by industry sector?
			Do accounting standards bodies influence the incorporation of BDA into the accounting curriculum?
		Organisations need special capabilities to face unforeseen changes in the marketplace.	How do different types of data analytics techniques predict performance in times of uncertainty?
	Prescriptive	Organisations need to take advantage of real-time information generated from advances in technology.	Does BDA truly create value: A longitudinal study of a manufacturing firm (Côte-Real <i>et al.</i> , 2019)
			How does BDA balance strategy, culture, and governance to affect business value creation?
			How beneficial are courses of action developed from prescriptive analytics for the organisation?
		The ease of embracing big data	How effective are BDA techniques as potential mediating factors of management change: A multi-case study of manufacturing companies (Vitale <i>et al.</i> , 2020)