Current Topics in Technology-Enabled Stroke Rehabilitation and Reintegration: A Scoping Review and Content Analysis

Katryna Cisek and John D. Kelleher

Abstract*— Background. There is a worldwide health crisis stemming from the rising incidence of various debilitating chronic diseases, with stroke as a leading contributor. Chronic stroke management encompasses rehabilitation and reintegration, and can require decades of personalized medicine and care. Information technology (IT) tools have the potential to support individuals managing chronic stroke symptoms. Objectives. This scoping review identifies prevalent topics and concepts in research literature on IT technology for stroke rehabilitation and reintegration, utilizing content analysis, based on topic modelling techniques from natural language processing to identify gaps in this literature. Eligibility Criteria. Our methodological search initially identified over 14,000 publications of the last two decades in the Web of Science and Scopus databases, which we filter, using keywords and a qualitative review, to a core corpus of 1062 documents. Results. We generate a 3-topic, 4-topic and 5-topic model and interpret the resulting topics as four distinct thematics in the literature, which we label as Robotics, Software, Functional and Cognitive. We analyze the prevalence and distinctiveness of each thematic and identify some areas relatively neglected by the field. These are mainly in the Cognitive thematic, especially for systems and devices for sensory loss rehabilitation, tasks of daily living performance and social participation. Conclusion. The results indicate that IT-enabled stroke literature has focused on Functional outcomes and Robotic technologies, with lesser emphasis on Cognitive outcomes and combined interventions. We hope this review broadens awareness, usage and mainstream acceptance of novel technologies in rehabilitation and reintegration among clinicians, carers and patients.

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Katryna Cisek is with the PRECISE4Q Project, Predictive Modeling in Stroke, Information Communications and Entertainment Institute, Technological University Dublin, Dublin 6, D07 EWV4 Ireland (e-mail: katryna.cisek@tudublin.ie).

John D. Kelleher is with the PRECISE4Q Project, Predictive Modeling in Stroke, ADAPT Research Centre, Maynooth University, Maynooth, Co. Kildare, W23 A3HY Ireland (e-mail: john.kelleher@mu.ie).

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I. Introduction

STROKE (the sudden interruption of blood supply to the brain) affects more than twelve million people worldwide annually, with up to one in five strokes occurring in young people aged 18 to 50 years [1], [2]. Moreover, the incidence of long-term complications and disabilities can strike up to half of all stroke survivors [3] and they may live with the consequences of stroke as chronic stroke sufferers for over twenty years [4]. Considering the years- and potentially decades-long duration of chronic stroke, the personalization of rehabilitation and reintegration programmes to maximize stroke recovery, and support patients adapting to their disabilities and returning to their daily life becomes a key consideration [5]. However, the personalization of rehabilitation and reintegration programmes (physical and cognitive exercises, tasks and activities) depends not only on the severity of post-stroke complications, but also on the specific clinical needs of the patients and their specific recovery goals and targets [6]. These can encompass complications stemming from physical and cognitive limitations as well as emotional and sensory disturbances compounded by other concurrent medical problems, the home and/or work environment of the patient, and most importantly, the age and post-stroke condition of the individual [7]. Taking into account these longitudinal and multi-factorial aspects of chronic stroke, various information technologies and "smart" devices integrating artificial intelligence (AI) algorithms have been increasingly employed for post-stroke patients [8]. These technologies enable personalized strategies during rehabilitation and reintegration, while monitoring and supporting patients over a long period of time, as well as empowering individuals with chronic conditions [9].

In the following scoping review, with the purpose of elucidating concepts and gaps in the field (as distinct from the aims of a systematic review) [10], [11], we address three main research questions: (a) what are the prevalent research topics in the field of IT-enabled stroke rehabilitation and reintegration? (b) how prevalent are each of these topics within the literature? (c) what are the gaps in the literature? We methodologically review the last two decades of literature focusing on IT-based technology support of post-stroke rehabilitation and reintegration, curating a corpus of over 1,000 original articles and clinical studies representing the current state of the field. The technology in the corpus specifically addresses IT, defined as any "smart" devices (robotics, sensors, computers), systems (software, artificial intelligence, brain computer interface), digital infrastructure (virtual reality environment) and processes (algorithms) to capture, analyse and utilize all forms of digital data. We set out to identify the prevalent themes in the stroke rehabilitation and reintegration literature utilizing topic modeling, in order to discover gaps in the field so as to galvanize future research in this area. The intended readership is not only researchers developing new technologies, but also clinicians and patients as we hope to broaden usage and mainstream acceptance of IT in rehabilitation and reintegration.

To the best of our knowledge, this work is the only application of topic modeling based content analysis to the technology-enabled stroke rehabilitation and reintegration literature spanning the last two decades. In a related work, "A survey of research trends in assistive technologies using information modelling techniques" [12], the authors identified 367 research papers in the area of technology-enabled rehabilitation stemming not only from stroke, but a constellation of chronic diseases and disabilities. Their information model identified five topics, "Wearable technologies for rehabilitation," "Smart assistive technologies," "Cloud-enabled rehabilitation services," "Neurological and cognitive rehabilitation," and "Multimedia applications for behavioural rehabilitation". Other rehabilitation and reintegration studies utilizing topic modeling focus on a specific technology, such as "Tracking the evolution of virtual reality applications to rehabilitation as a field of study" [13] and "Wearable activity trackers, accuracy, adoption, acceptance and health impact: A systematic literature review" [14]. Moreover, studies focused only on stroke are much narrower in scope, such as "Stroke Survivors on Twitter: Sentiment and Topic Analysis From a Gender Perspective" [15], "Activity routine discovery in stroke rehabilitation patients without data annotation" [16], and "Daily Life Activity Routine Discovery in Hemiparetic Rehabilitation Patients Using Topic Models" [17].

The scoping review is structured as follows: in Section II we provide an overview of the methodology we apply to curate a corpus of the research literature on stroke rehabilitation and reintegration, as well as provide an introduction to what topic modelling is and how we use it for content analysis; in Section III we describe our process for methodologically identifying relevant literature and the curation of our corpus for analysis; in Section IV we explain the data preparation we carried out prior to topic modelling, and the process we used to robustly identify research topics in the field; in Section V we describe how we qualitatively identify the content of each topic; and in Section VI we present our analysis of the distinctiveness and prevalence of the identified topics found in the literature. The paper concludes in section VII by describing the relative strength of association of the research articles in the corpus with the different thematics, the gaps in the literature that our analysis has revealed, and potential directions for future research.

II. Methodology

We use a four step methodology to answer our three main research questions. Our methodology begins with a structured search to create a representative corpus of relevant research literature (see Section III). This structured search identified over 14,000 papers which we filter using keywords and a qualitative review to a core corpus of 1062 documents.

Next we apply a topic modelling algorithm to segment this corpus of 1062 documents into coherent topics of research. Within natural language processing the concept of a topic is usually defined in terms of a group of words (tokens) that are likely to co-occur [18] and so share a non-taxonomic semantic association [19]. Consequently a topic can be understood as a set of words that frequently co-occur, and a document is considered to be about a topic if it contains a significant amount of words associated with a topic. Technically topic modelling is an unsupervised data mining technique from natural language processing. It is unsupervised because the target topics are not specified in advance, rather the analyst specifies (based on domain knowledge, or their intuition) the number of topics k the algorithm should look for in the data and then the topic modelling algorithm attempts to cluster the documents in a corpus into k groups (or topics) with the objective of maximising the terminology overlap between documents within the same topic (i.e., the intra-topic similarity) while at the same time minimising the terminology overlap between documents assigned to different topics (i.e., the inter-topic similarity) [20]. A key challenge with using topic modelling is deciding on the value for the parameter k which specifies the number of desired topics. Different values of k can result in very different segmentations of the corpus, in other words in the identification of very different topics [21]. We wish our topic analysis to be robust with respect to k, and so we run the topic modelling process 3 times each time with a different value of k (3, 4 and 5) and then look for topics that consistently appear across these three runs. To distinguish between a topic identified by a particular run of a topic model and a topic that consistently "emerges" across multiple topic model runs we use the term "thematic" to denote topics that persist across different runs of the topic modeling process. The comparison of topics across the three different runs of the topic modelling processing is based on terminological overlap: topics from different runs of the topic modelling process are considered to belong to the same thematic if there is a high-overlap between the sets of words that define the topics. The intuition motivating this between topic model comparison is that topics that persist across different values of k are more likely to represent real thematics of research in the literature. This computational (quantitative) analysis of the corpus is described in Section IV.

Once we have identified thematics that consistently appear across different topic models we move to the third stage of our methodology where we manually examine each of the thematics in turn in order to identify the content covered by these thematics. In this stage of analysis we use word clouds

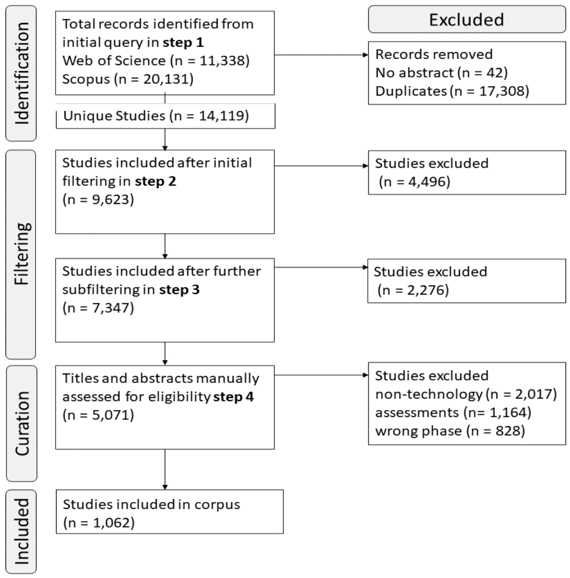

Fig. 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram for scoping review literature identification.

to visualise the terminology in each thematic and then use our knowledge of the domain to apply a descriptive label to each thematic that identifies the category of research carried out in that thematic.

In the final stage of our analysis we switch our focus from the structure of the thematics (in terms of the terminology associated with each thematic) to the relative prevalence of each thematic in the literature. To do this we label each document in the corpus with its most dominant thematic: note, that a document may contain words associated with different thematics, and so a document can be associated with multiple thematics, but the relative strength of association between a document and a thematic is dependent on the relative frequency of the words associated with the thematic in the document, as compared with the frequency of words from other thematics. Once each document has been labelled with a thematic we then analyse the relative prevalence of each thematic in terms of the number of documents belonging to each thematic. Finally, we determine the gaps in the field by plotting the 1062 documents based on the relative strength of association of the documents with different thematics on a coordinate plane.

III. Methodological Literature Search

The review of literature encompassing the last two decades (2000 - 2021) covers research indexed in the Web of Science and Scopus databases [22], [23]. In order to find relevant IT-enabled technologies utilized in stroke rehabilitation and reintegration, a structured search was performed on the titles and abstracts of the records identified in the literature search, filtered and curated according to specific inclusion and exclusion criteria (Fig. 1) in the following sequence of steps:

1) querying for “stroke rehabilitation”, “stroke reintegration”

2) filtering both query results with keywords “technology”, “device”, “system”, “application”, “software”, “platform”

3) further subfiltering the results using more specific keywords: “artificial intelligence”, “machine learning”, “algorithm”, “computer”, “robot*”, “wearable*”, “virtual”, “*game*”, “sensor*”, “stimulation”

4) manual curation to exclude assistive aide “technology” (canes, walkers), articles describing assessments and evaluations (no technology) and other studies outside of this scope

The reasoning behind using a variety of keywords for filtering the results stems from a lack of consistent terminology and the varied scope of the vocabulary in this domain. Moreover, additional keywords, such as “chronic stroke”, “management”, “outcome measure”, as well as “activities of daily living (ADL)” and “neurologist”, “therapist” and “clinician” were also searched, but they did not yield any additional results focusing on IT-technologies. However, certain trends became apparent within the scope of this keyword search, for example one terminology grouping was “chronic disease” and “management”, another “dementia” and “activities of daily living” and interestingly the use of keywords “neurologist” and “rehabilitation” identified literature for Parkinson’s disease. Moreover, not all hits returned references concerning technology. The step 1 initial literature search yielded over 14,000 hits, which were in steps 2+3 filtered with additional keywords to over 5,000 references, which in turn in step 4 were manually curated in order to identify 1062 references suitable for this review focused on stroke rehabilitation and reintegration technologies. Raters reviewed the studies separately against inclusion and exclusion criteria and studies without the consensus of both raters were excluded. Articles describing non-technology frameworks and concepts (e.g., scales and scoring systems), physician administered assessments and questionnaires as well as those pertaining to the prevention and acute treatment phases were excluded.

IV. Quantitative Content Analysis Using Topic Modelling

Once we had curated our core corpus of research documents the next stage in our methodology involved clustering these documents into coherent and robust topics. Latent Dirichlet Allocation (LDA) [24], [25] topic modelling was used for a high-level analysis of the corpus of 1062 documents retrieved through the literature search, and through this analysis to find the relevant themes and gaps in the field.

A topic model defines a mapping between documents and topics in terms of how closely associated a document is with a topic. Topics models generally identify repeating patterns of co-occurring words across documents – a topic is essentially a group of words that frequently co-occur together – and the mapping between a topic and a document is based on mapping between the distribution of words within the document and the identified topics (the groups of co-occurring words) identified by the algorithm. Although a topic modelling algorithm can automatically identify sets of co-occurring words, it is the task of the human analyst to check that the identified sets of co-occurring words do indeed represent coherent topics and also to ‘label’ what these topics are [20]. Where the analyst deems that the identified topics are not coherent the topic modeling process can be rerun with different parameters to identify new sets of co-occurrence patterns. Consequently, topic modelling is an iterative human-in-the-loop methodology.

In some topic models a document can only be associated with one topic, however, within an LDA topic model a document can cover multiple topics. Furthermore, an LDA topic model also defines a mapping between terms and topics, and (similar to documents) a term can be associated in multiple topics. More specifically, an LDA topics model defines a separate probability distribution over topics for each document and terms in the corpus. The probability distribution over topics for a document describes to what extent a document is 'about' each topic, and the probability distribution for a term describes the strength of association between that term and each topic [20], [24], [25].

In our topic modelling based analysis of the literature we use the concept of a thematic to identify coherent sets of concepts that recur across multiple papers in the corpus. Topic modelling is an unsupervised process that requires the human analyst to guess the number of topics in the corpus, and the outcome of the topic analysis is naturally sensitive to the number of topics looked for. Consequently, in order to identify coherent sets of thematics in the corpus we created three different topics models with different numbers of topics in each model (topic model one had 3 topics, topics model two had 4 topics and topic model three had 5 topics) and then looked for topics that persisted across these different topic models. The intuition here being that thematics that are consistently present across different topic models are more likely associated with thematics that are truly present in data. To identify these consistent thematics we calculated a similarly score [26], [27] between the topics identified in the 3-, 4- and 5- topic models.

The comparison of the topics within each topic model internally and between topic models (e.g. topic 1 of 3-topic model to topic 2 of 4-topic model) was performed using the cosine similarity of the term index rankings in each topic [26], [27]. Cosine similarity is a metric used to measure how similar two vectors are. Mathematically, it measures the cosine of the angle between two vectors projected in a multi-dimensional space - if the angle is small, the vectors are similar, if it is large, the vectors are dissimilar. In our analysis we use cosine similarity to calculate the similarity between a pair of topics by calculating the similarity between vectors describing the LDA generated term-topic probability distributions after the terms in the vectors have been aligned by being alphabetically organised. Consequently, each dimension in the space where the cosine similarity is measured measures the probability (relative to the other terms in the vocabulary) of a given term occurring in a document belonging to a topic, and so topics that have a similar probability distribution across their terms will have small angle between their vectors and so will be considered similar. This cosine similarity approach to topic similarity is feasible here because in an LDA topic model all topics have the same number of terms associated with them (the vocabulary of the entire corpus the LDA topic model was run on) the distinction between topics being how these terms are ranked (in terms of strength of association) for each topic [20], [24], [25]. To generate the vector representation of each topic used in the cosine similarity calculation the term index ranking vector for each topic was extracted using the terms() function [26], [27], then for each topic its ranked terms were then sorted alphabetically, and the vector containing the alphabetically sorted term ranks was used to represent the topic. Using the cosine similarity across topics allows us to identify similar topics across different topic models, and thereby to find thematics that consistently appear across different topic modelling.

In subsection A we describe the data preparation and the creation of the different topic models. Following this, in subsection B we describe how we carried out the inter-topic model comparison to identify consistent thematics in the literature.

A. Data Handling and Implementation

To implement the topic modelling analysis we used the R statistical software [18], [28] packages revtools() [29], litsearchr() [30], topicmodels() [31], tm() [32], [33] and wordcloud() [34]. The topic modeling was applied to the titles and abstracts of the 1062 references identified in the literature search and included the following sequence of steps:

1) pre-processing the corpus to remove numerical values, punctuation, sparse terms, as well as English functioning words as non-domain specific stopwords (e.g., the, is, of, and)

2) scanning the pre-processed text using the Rapid Automatic Keyword Extraction (RAKE) algorithm [35] in order to identify multiple-word phases based on words which frequently co-occur together (2 or more words, occurring at least 10 times in the corpus), identifying 364 frequent two to four word phases

3) tagging multiple word phrases in the corpus (using underscore "_" delimiter) according to the following criteria:

a) merging multi-word phases denoting the same concept (e.g. merging plural, singular and grammatical forms; "wearable robot", "wearable robots" and "wearable robotic" were merged under a single concept "wearable_robot")

b) tagging on the basis of manual qualitative analysis where phrases denoting the same concept are merged (e.g. merging "lower extremity" and "lower limbs" under a single concept "lower_extremity"), tagging unique multiple word phases under their own concept (e.g., tagging "artificial intelligence" as "artificial_intelligence"), and

c) not tagging (leaving as single words) frequently co-occurring words not relevant to this domain (e.g. "study showed", "significant difference" and "paper describes") or too broad/general within this domain ("clinical trial", "stroke rehabilitation" and "stroke patients")

4) lemmatizing* [36] the whole corpus to the base or dictionary form of a word using the tm_map() function of tm package (stemming – removing the last few characters of a word – was also performed instead of lemmatization in a parallel procedure and results compared; we found no significant difference in our overall results when we switch between lemmatization and stemming and so we only report the results for lemmatization)

5) creating a document term matrix (DTM) [20], [37] with a row for each document in the corpus and a column for each tagged and single term in the vocabulary of the corpus. Automatically calculating term sparcity, as each cell in the DTM records whether the document represented by the cell row contains the term represented by the cell column (a cell value is zero if the term does not occur in the document, otherwise it's the count of the term in the document)

6) removing the most frequently occurring terms (e.g., "stroke", "patients", "rehabilitation", "using", "training", "system", "study") occurring more than 500 times, as well as the most sparse terms occurring only once in the corpus (e.g. "licensee", "southeastern", "survival", "victim")

7) building three different LDA topic models from the lemmatized DTM (1062 documents x 1343 final terms), containing three, four and five topics with corresponding probability distributions over the topics for each document

Following the generation of the 3-, 4-, and 5-topic model we identify consistent thematics (i.e., topics that recur) across the three topic models on the basis of term ranks. To do this we use the LDA-derived term ranks for each topics and cosine similarity scoring of these term ranks to identify similar topics across the three topic models in order to align and identify consistent thematics. We describe process and results for this inter-topic model comparison in the next section.

B. Quantitative Alignment of Topics (Based on Cosine Similarity)

In building several topic models in order to identify the high level thematics and concepts, the resulting 3-, 4-, and 5-topic models yielded 12 topics altogether. We then applied the cosine similarity metric [26], [27] in order to compare topics to each other within a model and gauge topic overlap, as well as between models to identify which topics are similar between models.

Specifically, we utilized the cosine similarity [26], [27] of the term index rankings in each topic (for each topic, terms were sorted alphabetically, and the sorted index vectors used for cosine similarity calculation). Within each topic model, topics were fairly distinct from each other (cosine similarity between 0.74 and 0.80), with the exception of topic 5 of the 5-topic model; the terminology of this topic most strongly characterized clinical study design within this field, not surprisingly overlapping more strongly with other topics which also contained clinical studies (cosine similarity between 0.77 and 0.87). Table I lists the cosine similarity between all topics.

Moreover, by looking for topics from the different topic models the 3-, 4- and 5-topic models that have a high cosine similarity, we are able to identify topics that robustly emerge from the data across different values of k. This analysis reveals that following groupings of topics (or thematics) across the topic models:

1) 3-topic model topic 1 [3-1] has a high cosine similarity with both the 4-topic model topic 3 [4-3] and the 5-topic model topic 1 [5-1] (cosine similarity 0.96; bolded), but has a relatively low similarity to all other topics (cosine similarity between 0.70 and 0.87). Furthermore, the 4-topic model topic 3 [4-3] and the 5-topic model topic 1 [5-1] are highly similar to each other (cosine similarity 0.99; bolded). This suggests that these three topics describe the same research thematic.

2) 3-topic model topic 3 [3-3] has a highly similar terminology with 4-topic model topic 1 [4-1] and 5-topic model topic 2 [5-2] (cosine similarity 0.94; bolded) but is less similar to all other topics (cosine similarity between 0.72 and 0.87); and 4-topic model topic 1 [4-1] and 5-topic model topic 2 [5-2] are quite similar to each other (cosine similarity 0.92; bolded). This suggests that these three topics all identify the same research thematic.

3) 3-topic model topic 2 [3-2], 4-topic model topic 2 [4-2] and 5-topic model topic 3 [5-3] with very similar terminology (cosine similarity 0.94 and 0.96, respectively; bolded) and less similar to other topics (cosine similarity between 0.75 and 0.83), as well as 4-topic model topic 2 [4-2] and 5-topic model topic 3 [5-3] being very similar to each other (cosine similarity 0.96; bolded). Again this suggests that these three topics can be considered to describe the same research thematic.

4) 4-topic model topic 4 [4-4] and 5-topic model topic 4 [5-4] had very similar terminology (cosine similarity 0.94; bolded), and dissimilar to other topics (cosine similarity between 0.74 and 0.81). We consider these two topics as identifying the same research thematic within their respective topic models.

5) finally, 5-topic model topic 5 [5-5] had a cosine similarity between 0.77 and 0.87 with other topics.

V. Qualitative Interpretation of Topics Based on Terminology

Having identified the thematics that recur across the three topic models we manually inspected the top-ranked terminology associated with each topic in a thematic in order to qualitatively interpret the thematic. Visual inspection of more than 30 top-ranked terms in the wordclouds Fig. 2 in each of the 12 topics enabled us to label each thematic as follows:

1) Thematic 1: the top-ranked terms in topics [3-1], [4-3], and [5-1] are associated with motor/physical rehab utilizing robotics (top-ranked terms: assist, robot, exoskeleton, force, actuate, muscle, and active) and so we named this thematic of topics "Robotics",

2) Thematic 2: the top-ranked terms in topics [3-3], [4-1], and [5-2] were associated with cognitive rehab utilizing virtual reality and games (top-ranked terms: cognitive, game, virtual reality, engage, user, intervention) and so we labelled this thematic of topics "Cognitive",

3) Thematic 3: the top-ranked terms in topics [3-2], [4-2], and [5-3] were associated with rehab monitoring classifiers and algorithms utilizing sensory data (top-ranked terms: sensor, algorithm, feature, model, accuracy, and signal) and so we categorized this topic thematic as "Software",

4) Thematic 4: this fourth theme did not emerge in the 3-topic model, but the topic-ranked terms in topics [4-4] and [5-4] were associated with sensory-motor functional rehabilitation utilizing brain stimulation (top-ranked terms: motor, feedback, sensory, function, tool, recovery, potential) and so we labelled this thematic as "Functional",

TABLE I
COSINE SIMILARITIES CALCULATED BETWEEN 12 TOPICS IDENTIFIED BY TOPIC MODELS

		3-topic model			**4-topic model**				**5-topic model**				
	Topics	[3-1]	[3-2]	[3-3]	[4-1]	[4-2]	[4-3]	[4-4]	[5-1]	[5-2]	[5-3]	[5-4]	[5-5]
3-topic model	[3-1]	1	0.79	0.74	0.70	0.84	**0.96**	0.83	**0.96**	0.76	0.82	0.73	0.87
	[3-2]		1	0.77	0.79	**0.94**	0.76	0.80	0.77	0.75	**0.96**	0.83	0.80
	[3-3]			1	**0.94**	0.72	0.75	0.80	0.74	**0.94**	0.74	0.87	0.87
4-topic model	[4-1]				1	0.75	0.74	0.78	0.73	**0.92**	0.75	0.85	0.77
	[4-2]					1	0.80	0.77	0.81	0.71	**0.96**	0.79	0.81
	[4-3]						1	0.79	**0.99**	0.76	0.78	0.76	0.83
	[4-4]							1	0.79	0.74	0.81	**0.94**	0.81
5-topic model	[5-1]								1	0.76	0.80	0.76	0.81
	[5-2]									1	0.76	0.77	0.84
	[5-3]										1	0.77	0.81
	[5-4]											1	0.77
	[5-5]												1

5) Thematic 5: examining the topic-ranked terms in topic [5-5] revealed them to be general terminology describing clinical study design in this field (top-ranked terms: intervention, session, treatment, outcome, improvement, feasible), and so we named this thematic "Study-design".

Due to the high overlap of the top-ranked terms in the 3-, 4-, and 5-topic models, here we use word clouds to visualize the terms in the five topics in the 5-topic model only, which align with these five thematics: [5-1] Robotics, [5-2] Cognitive, [5-3] Software, [5-4] Functional, and [5-5] Study-design (Fig. 2).

VI. TOPIC PREVALENCE AND DISTINCTIVENESS

Building on our identifying and interpretation of the research thematics in the literature in this section we first analyze the relative prevalence of each thematic in the publications, and then we analyze the similarity across thematics. We analyze the prevalence of each thematic in terms of the number of documents associated with that thematic's topic in each of the models, and we analyze the similarity across thematics by examining a document confusion matrix between thematics as documents transition from the 3-topic to the 5-topic model. In order to carry out both of these analyses we must first map each document to its most relevant topic for each of the three topic models. The LDA algorithm generates topics by assigning probabilities to the document terms associated with that topic, thereby mapping each document to several topics. Each document is considered to be a mixture of all topics, e.g., for the 3-topic model, each document is a mixture of three topics, with the mixture of topics in the document expressed as a probability distribution across the three topics, whereas for the 5-topic model, each document is a mixture of five topics, expressed as a probability distribution across five topics [20], [24], [25]. In order to map documents to topics, we focused on the highest probability topic for each document.

With respect to the relative prevalence of each thematic Table II summarizes the 1062 document distribution for the three topic models generated. Consistently for all models, the Robotics and Cognitive technologies thematics contain the most documents, except for Software having more documents than the Cognitive thematic in the 5-topic model. However, our analysis of the confusion of thematics across topics models (presented below) revealed that many of the Cognitive thematic documents are clinical studies, with many of them transitioning to Study-design documents in the 5-topic model.

In order to assess the similarity of research across the different thematics we created a confusion matrix [37] between the 3- and 5-topic models based on the document categorization by thematic under each of these topic models. We chose the comparison between the 3-topic and 5-topic models as they have the most dissimilar distribution of documents in the different topics and therefore most clearly show the transition of documents between thematics. Table III presents this confusion matrix. The confusion matrix shows the distribution of documents within the same thematic for both models, as well as the occurrence of documents which transition from the origin 3-topic model to another thematic in the 5-topic model. The diagonal top-left to bottom-right indicates the distribution of documents consistently classified as the same thematic in the 3-topic and 5-topic models. For both the Robotics and Cognitive thematics, 99% and 97% of documents, respectively, are consistently classified. For the Software thematic, 66% of documents are consistently classified, whereas a third are not - in many cases owing to the fact that those documents have high probabilities of belonging in more than one thematic (overlapping two or more thematics). Entries off the diagonal of the confusion matrix show which documents transition from their original thematic in the 3-topic model to another thematic in the 5-topic model; for example, 52 Software documents in the 5-topic model transitioned from the Robotics thematic of the 3-topic model (i.e., the Robotics thematic is the most frequently confused thematic for Software). This is likely because many algorithms described in the documents utilize sensor data which tracks movement, frequently also describing a wearable robotic device. Similarly, for the Robotics and Cognitive confused documents, 3 transition to Robotics and 6 transition to Cognitive; these documents indeed overlap the thematics (e.g., "Design of Virtual Guiding Tasks With Haptic Feedback for Assessing the Wrist Motor Function of Patients With Upper Motor Neuron" [38], "Validation of the reasoning of an entry-level cyber-physical stroke rehabilitation system equipped with engagement enhancing capabilities" [39], respectively). In the 3-topic model, there were no Functional or

Fig. 2. Word clouds of the top-ranked 100 terms of the 5-topic model for each of the five topics recapitulating the main thematics: a) [5-1] Robotics, b) [5-2] Cognitive, c) [5-3] Software, d) [5-4] Functional, and e) [5-5] Study-design.

TABLE II
NUMBER OF DOCUMENTS PER RESEARCH THEMATIC ACROSS THE 3-TOPIC, 4-TOPIC, AND 5-TOPIC MODEL

	Model Thematics				
	Robotics	Cognitive	Software	Functional	Study-design
3-topic model	392	438	232	NA	NA
4-topic model	240	251	260	311	NA
5-topic model	247	188	232	159	236

Study-design thematics, therefore, the last columns show the distribution of these documents identified by the 5-topic model transitioning from the 3-topic model. For example, 180 of the documents categorized as being about Cognitive research by the 3-topic model are categorized as describing Study-design in the 5-topic model.

Most documents transitioned to the Functional and Study-design thematics from the Cognitive thematic. However, for over 60% of these articles, although the Cognitive thematic had the highest probability, the Robotics thematic was a close second ranking, and less frequent, the Software thematic was also a close second. This indicates that although the Robotics, Cognitive, and Software thematics persist from the 3-topic model to the 5-topic model, the Functional and Study-design thematics are highly related to all of these thematics and rather than being a specialization of a particular thematic, they are new standalone thematics. For the 4-topic model (not shown), there is a greater separation of the Robotics and Cognitive thematics, with one trend showing that for documents classified as Robotics, Functional thematics, rather than Cognitive, was close behind. In the 5-topic model, a topic representing terminology of the study-design emerges, in which the documents span all the other thematics (Robotics, Functional and Cognitive), however the prevalence of the terminology describing clinical study design dominates this thematic.

In general, the Functional and Robotics thematics overlap due to many of the research articles describing smart clothing and stimulation devices which are confused as Robotics, for example, “Garments for functional electrical stimulation: Design and proofs of concept” [40], “Technical development of transcutaneous electrical nerve inhibition using medium-frequency alternating current”, “Functional electric stimulation therapy” [41], “On the road to a neuroprosthetic hand: A novel hand grasp orthosis based on Functional Electrical Stimulation” [42]. On the other hand, the Software and Cognitive thematics have less overlap and most documents are classified consistently, for example, “The Application Analysis of Neural Network Techniques on Lexical Tone Rehabilitation of Mandarin-Speaking Patients With Post-Stroke Dysarthria” [43] and “Detection and Classification of Stroke Gaits by Deep Neural Networks Employing Inertial Measurement Units” [44] as Software; “Circadian Preference and Facial Emotion Recognition Among Rehabilitation

TABLE III
CONFUSION MATRIX ACROSS THEMATICS DEFINED IN THE ORIGINAL 3-TOPIC AND TRANSITIONING TO THE 5-TOPIC MODEL IN TERMS OF THE CLASSIFICATION OF DOCUMENTS

3-topic model		5-topic model					
		1	2	3	4	5	
	Thematics	Robotics	Cognitive	Software	Functional	Study-design	**Total**
1	Robotics	244	6	52	83	7	392
2	Cognitive	3	182	6	67	180	438
3	Software	0	0	174	9	49	232
4		0	0	0	0	0	
5		0	0	0	0	0	
	Total	247	188	232	159	236	

Inpatients" [45] and "Screening and patient-tailored care for emotional and cognitive problems compared to care as usual in patients discharged" [46] and "Competitive and cooperative arm rehabilitation games played by a patient and unimpaired person: effects on motivation and exercise intensity" [47] as Cognitive. Robotics research describing robotic devices is also consistently classified as Robotics, for example "Planar robotic systems for upper-limb post-stroke rehabilitation" [48] and "Intelligent Medical Rehabilitation Training Instrument Based on Movement Coordination" [49]; Functional, "Progress in Brain Computer Interface: Challenges and Opportunities" [50] and "Towards BCI-actuated smart wheelchair system" [51].

VII. ASSOCIATION OF DOCUMENTS WITH DIFFERENT THEMATICS

This scoping review of IT-based stroke rehabilitation and reintegration publications of the last two decades reveals that the literature can be categorized into four distinct thematics utilizing topic modeling: Robotics, Cognitive, Software, and Functional. Because Study-design reflects the methodology of the publication rather than its topic domain and highly overlaps with the four thematics (Robotics, Software, Functional and Cognitive), the 4-topic model was chosen over the 5-topic model for the analysis. Fig. 3 depicts the distribution of the publications per year for 2001-2021 by thematic; for simplicity we grouped the years as follows: 2018-2021, 2014-2017, 2010-13, and 2001-2009 in one group because in these years there are relatively few publications (Fig. 2ab). Along with the distribution of studies that varies from year to year, the distribution of the thematics is dominated by Functional studies in the initial years, until the most recent. 2018-2021, showing a more balanced proportion of each thematic, especially where depicted as a percentage of studies (Fig. 2c). Therefore, although it is clear that the Functional thematic is prevalent especially in the initial years, the other thematics are also present and so we do not consider them as emerging topics.

The Cognitive and Functional thematics are related to patient outcomes and can be understood as defining opposing poles of concern along an axis, and the other two thematics, Software and Robotics, are related to technologies used to support rehabilitation and reintegration. Using these domains of Patient Outcome and Technology we can designate a 2D space where each axis defines the relative strength of association of a document with the relevant thematics in that domain. Using this 2D space we then plotted each study on a coordinate plane (using the topic probabilities from the 4-topic model) to show the distribution of the literature (Fig. 4) and to identify thematic gaps in this area of research. The distribution of the documents on the plot is denser on the right side than the left, indicating that most of the curated literature falls under the Functional rather than the Cognitive thematic. Moreover, there is a clustering of documents on the x axis but not on the y axis, suggesting that there is a stronger separation in research on patient outcomes (Cognitive vs. Functional) as compared with technology (Robotic vs. Software) with a number of papers discussing both and hence being plotted on the x-axis.

The thematic clustering of works in the top corner (around coordinates 0,1) mainly describes design, development and testing of robotic joints, gloves and wearable exoskeletons spanning the Robotics theme focused on various physical devices for motor rehabilitation [52], [53], [54], [55], [56].

The cluster of publications in bottom corner (around coordinates 0,−1) describes the detection, estimation and tracking of motion mainly attributed to gait and movement of limbs, utilizing wearable inertial sensors (e.g. accelerometers and gyroscopes) spanning mostly the Software theme describing different systems for mainly patient fuctional rehabilitation [57], [58], [59].

The cluster of works in the left corner (around coordinates −1,0) focuses on video, computer game and virtual reality cognitive rehabilitation, as well as combining cognitive rehabilitation with wearables, exoskeletons and devices for gait and motor training, spanning mainly the Cognitive theme and patient neurorehabilitation needs. In contrast to Robotics and Software, there is a clustering of studies on the axis; this is most likely indicative of the fact that most of these studies are clinical trials (also supported by confusion matrix result, where most Cognitive studies transitioned to the Study-design thematic) [60], [61], [62].

The literature clustered in the right corner (around coordinates 1,0) describes frameworks, tools and devices, such as brain-computer interfaces and virtual reality, for balance and motor neurorehabilitation, as well as aphasia rehabilitation, of the Functional outcome domain that addresses patient physical needs and challenges. As in the case of the Cognitive thematic, there are also numerous clinical trial studies clustered around the axis [46], [63], [64].

The literature in the upper right quadrant (around coordinates 0.3, 0.5) is a combination of Functional and Robotic thematics, including robotic orthosis, wearable robots, BCI-systems and sensors for various neuro- and functional

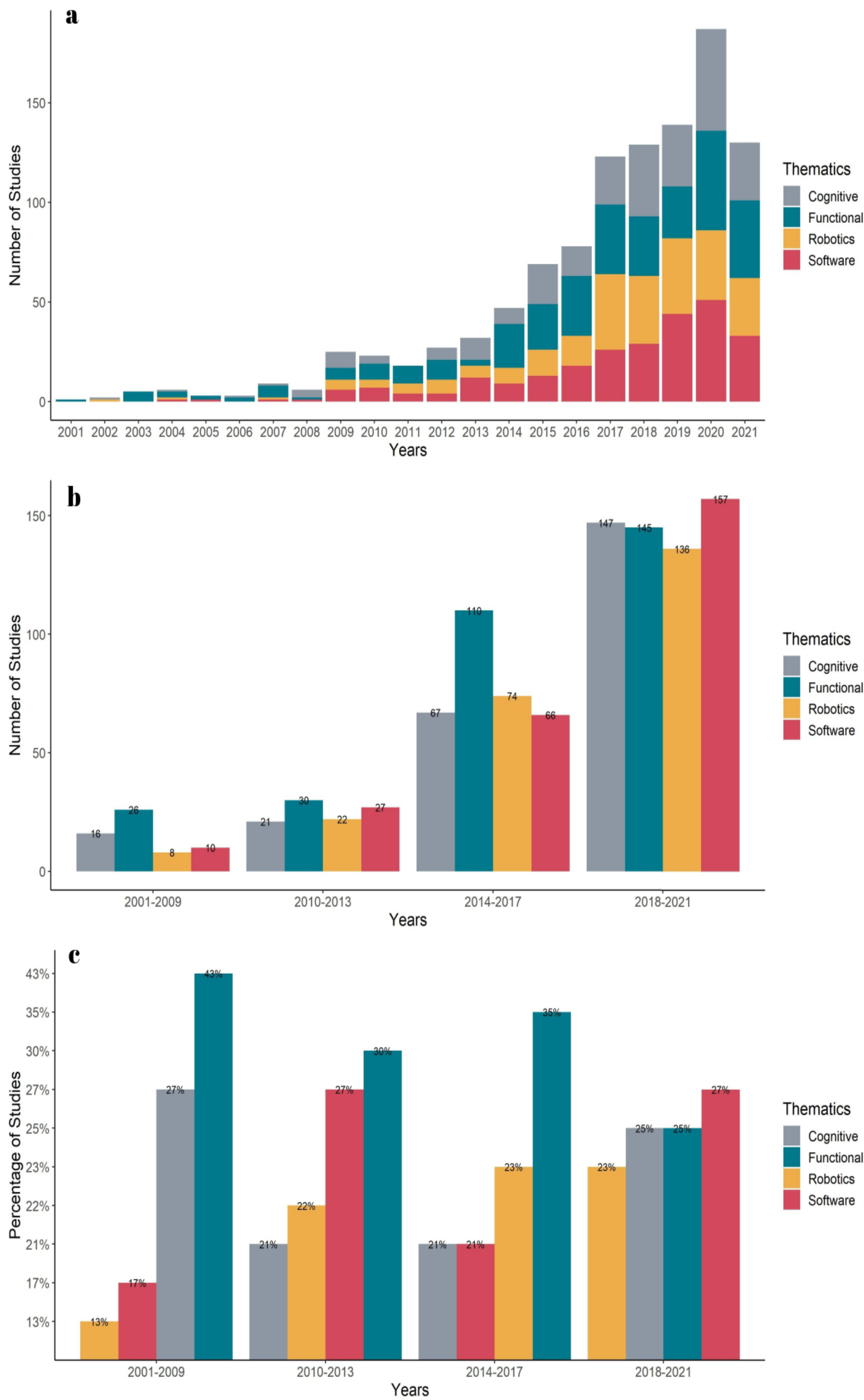

Fig. 3. The final corpus of the systematic literature search showing the distribution of the 1062 studies published a) per year b) binned into year groups c) as percentage in year group.

rehabilitation; while the literature in the lower right quadrant (around coordinates 0.3, −0.5) is a combination of the Functional and Software thematics, including the application of gadgets and technologies, such as wearable robotics and sensors as well as smart devices to improving functional independence [65], [66], [67].

In contrast, there appear to be gaps in the literature specifically in the left quadrants, encompassing the Cognitive thematic, especially in the upper left quadrant (around coordinates −0.3, 0.5) in the overlap of the Robotics and Cognitive domains where a few references mainly describe systems and devices aimed at improving upper limb function, as well as

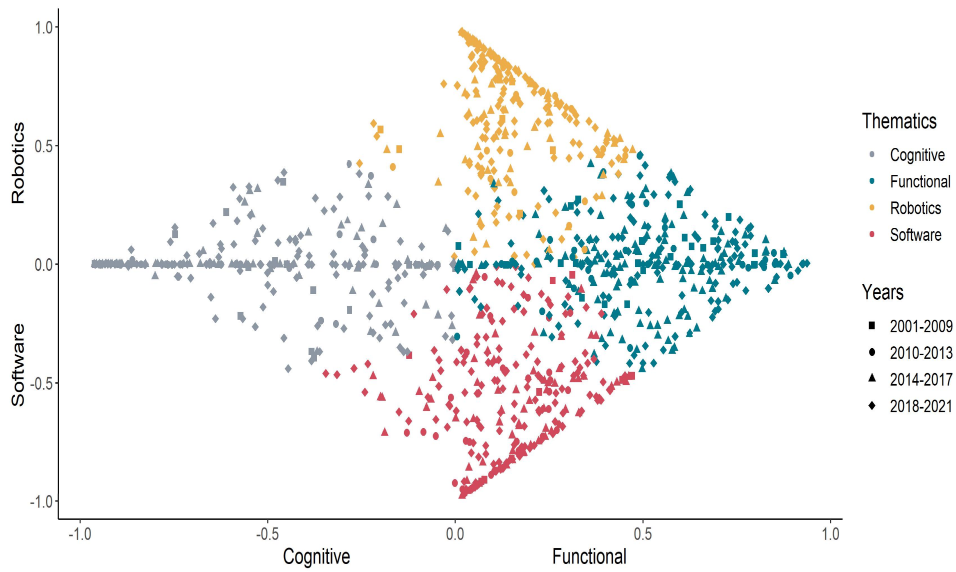

Fig. 4. Scatterplot of 1062 publications based on the relative strength of association of the documents with different thematics.

mentioning sensory loss rehabilitation [68], [69]. We have not been able to identify any studies focused on sensory loss rehabilitation after stroke utilizing a combined approach of robotic-assisted and cognitive therapies, and very few studies for such combined interventions for upper limb function improvement. Therefore, the clinical implications of such few studies at the interface of the Robotic and Cognitive thematics indicate that interventions combining robotic-assistive and cognitive therapies, for example, an upper limb exoskeleton linked with a virtual reality gaming environment, are a largely understudied topic, but have the potential of compounded positive effects and better rehabilitation outcomes for patients.

Additionally, publications are sparse in the lower left quadrant (around coordinates −0.3, −0.5) in the overlap of the Software and Cognitive thematics, where current literature describes algorithms, tools and systems enabling the rehabilitation of patients to improve independence in performing tasks of daily living (both cognitive and physical) as well as social participation [70], [71], [72], [73]. Because tasks of daily living as well as social participation are very complex behaviours, highly specialized systems implementing sophisticated AI components would be needed to predict and anticipate human interactions, and a strong evidence base would be needed to show their effectiveness in clinical practice. Although VR has been hailed as a modern rehabilitation tool that could bridge the interface across all four thematics (e.g., virtual reality environment linked with robotic devices, wearable sensors, and garments for functional electrical stimulation), currently such complex systems may not be feasible nor cost-effective for implementation in the clinic [13].

In summary, we have identified gaps in the literature at the interfaces (overlaps) of the thematics, specifically the overlap of the Cognitive thematic with Robotics and Software. This indicates that most post-stroke rehabilitation and reintegration interventions, especially neurorehabilitation, mainly concentrate on a single form of therapy, rather than combining protocols within the same rehabilitation programme. Currently, there is insufficient evidence regarding the benefit of such combined approaches, as well as a lack of clinical implications for interventions targeting multidimensional clinical needs, such as social participation [74].

VIII. Conclusion

In the last two decades the stroke rehabilitation and reintegration literature has focused mainly on the Functional needs of patients with Robotic devices. However, in the Software and especially the Cognitive thematics there appear to be gaps in the literature, especially for systems and devices for sensory disturbances rehabilitation, improvement of tasks of daily living performance and social participation. Although we have curated a very large corpus of over a thousand original articles, which was crucial to identify these gaps in the usage of information technology after stroke, nevertheless, there is a lack of standardised terminology and definitions for what constitutes information technology in this field. Therefore, the usage of specific keywords to identify and filter article titles and abstracts limited the scope of our search to publications containing this terminology. Additionally, while the integration of topic modeling into the methodology facilitated the analysis of a very large corpus, a potential limitation is that the interpretation of topics to thematics is a manual step based on top-ranked terms and domain knowledge, and therefore is somewhat subjective.

We hope this review not only informs researchers developing new technologies on current directions of research in the field, but also broadens awareness, usage and mainstream acceptance of IT and "smart" devices in rehabilitation and reintegration among clinicians, carers and patients. We recommend conducting a systematic review on information technologies used in stroke rehabilitation and reintegration phases, which adheres to a structured and pre-defined process to identify where technologies are used in combination therapies, overlapping two or more thematics (Cognitive, Functional, Software and Robotics). Such a systematic review would not only advance stroke rehabilitation science but also provide a strong evidence base for mixed information technology interventions.

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