Journal of Business Research 131 (2021) 591–597

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri

Rajibul Hasan[a,*], Riad Shams[b], Mizan Rahman[c]

[a] Maynooth University, Ireland
[b] Newcastle Business School, UK
[c] Lincoln International Business School, UK

ARTICLE INFO

Keywords:
Voice-controlled artificial intelligence
Trust
Risk
Siri

ABSTRACT

Artificial intelligence (AI) has the potential to change consumer behavior. However, despite billions of consumers using mobile smart phones, adoption of (artificial) intelligent voice assistants, like Siri, is relatively low. A conceptual model was constructed to determine the influence of consumer trust, interaction, perceived risk, and novelty value on brand loyalty for AI supported devices. Using the MTurk platform, data was collected from a sample of 675 Apple iPhone-using respondents. The findings showed perceived risk seems to have a significantly negative influence on brand loyalty; however, other factors were found to have a significantly positive influence on brand loyalty. The influence of novelty value of using Siri was found to be moderated by brand involvement and consumer innovativeness in such a way the influence is greater for consumers who are less involved with the brand and who are more innovative.

1. Introduction

Historical research in the area of adoption and behavioral intentions has yielded many competing models (e.g., Diffusion of Innovations: Rogers, 1962; the Theory of Planned Behavior [TPB]: Ajzen, 1991; the Technology Acceptance Model [TAM]: Davis, 1993), and each has different sets of acceptance determinants. Among these, the Theory of Planned Behavior is an augmented model of the Theory of Reasoned Action (Fishbein & Ajzen, 1975), which lacks perceived behavioral control as one of its elements.

Separately, for this paper's purposes, the core concept of artificial intelligence (AI) is defined as the science and engineering of machines that act intelligently (Norvig, 2012). AI allows one to analyze and learn from vast amounts of data and use the data to make future predictions. Existing use of technology-mediated platforms, like Amazon, enable marketers to analyze customers' data and make predictions about what products the customers might buy in the near future (Morgan, 2018; Shams, & Solima, 2019).

AI has taken this data analysis one step forward as, for example, with Apple's Siri. This intelligent assistant's software can interpret voice commands, pick up keywords speakers use, and, subsequently, execute a set of built-in commands and responses (Hoy, 2018). No longer in its infant stage, the software is now connected to the Internet and is able to access personal information stored on the phone and is enabled to predict and respond to users' requests and inquiries, providing the user the desired information. After its activation, the device gradually interprets a user's voice as a command. As time progresses, the software's information base becomes richer and can understand and interpret a user's commands in a more intelligent way, and thus its ability to provide a number of services increases (Hoy, 2018).

To contribute to this literature on new technology adoption and investigate its nuances, consumer trust, interaction, perceived risk, and novelty value were identified as influences on the voice-controlled artificial intelligence called Siri. New discussions around trust, ethics, data collection, usage, and privacy issues (Jones, 2018) have surfaced since the Facebook data-breach scandal in 2018. Just before the scandal, consumers were also feeling a bit conflicted in general about whether to adopt new technologies (Chung, Iorga, Vaos, & Lee, 2017). Although digital product usage and online consumption is on the rise, it has become an existential threat for some brands in the digital era who have had to focus on rebuilding trust with consumers to assure their privacy and personal information use is not compromised (Lombardi, Giudice, Caputo, & Evangelista, & Russo, 2016; Trequattrini, Shams, Lardo, & Lombardi, 2016; Lombardi, Rossi, & Russo, 2012). Some authors

* Corresponding author at: School of Business, School of Business Building, North Campus, Maynooth University, Maynooth, Co. Kildare, Ireland.
E-mail address: Rajibul.Hasan@mu.ie (R. Hasan).

https://doi.org/10.1016/j.jbusres.2020.12.012
Received 1 March 2020; Received in revised form 28 November 2020; Accepted 2 December 2020
Available online 19 December 2020
0148-2963/

emphasize trust is essential for effective relationship management in marketing (Sekhon, Ennew, Kharouf, & Devlin, 2014). Therefore, given this issue, this study aims to understand how to improve brand adoption and, in turn, brand loyalty of such AI-driven products like Siri.

In the context of this research, we must recognize benefits from AI are transcendental if one considers the potential for social utility. It has the potential to lower the barriers to adoption and usage, thus providing significant gains for society. A large population of the world are still illiterate or cannot physically type; thus, AI could potentially bridge the information gap for them. Moreover, for consumers with certain health conditions like dementia and may ask repetitive questions and need constant support, AI could give immense opportunities to improve their conditions by providing them with a much better and independent lifestyle (Hoy, 2018).

2. Literature review

Many models have been offered to explain consumers' adoption of new products, and these typically focus on cognitive evaluations. Generally, most research is built upon the Technology Acceptance Model (TAM) (Davis, 1989), Rogers' (2003) Diffusion of innovations (DOI), or the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975). In consumer adoption literature, the innovation's perceived attributes and the adopter's characteristics are recognized as important drivers of consumer adoption (Gatignon & Robertson, 1985; Rogers, 2003; Tornatzky & Klein, 1982). Adopter characteristics represent the personal traits, including psychographic and sociodemographic, that explain an innovation adoption. Previous research (e.g., Gatignon and Robertson, 1985; Rogers, 2003) has identified a wide variety of sociodemographic characteristics, some of which specifically focus on consumers' educational levels, ages, and incomes. Other variables often considered include gender, household size, and family life cycle.

Psychographic characteristics are also useful predictors of innovation adoption based on one meta-analysis in the area (Arts, Frambach, & Bijmolt, 2011). Typical psychographic characteristics include innovativeness, media proneness, opinion leadership, and involvement (Lowe & Alpert, 2015). In addition, one major driver of consumer adoption, innovation attributes, which refers to the characteristics consumers use to evaluate an innovation, are normally represented by a consumer's perception of the relative advantage, complexity, compatibility, trialability, observability (Rogers, 2003), and risk or uncertainty (Hoeffler, 2003; Ostlund, 1974) of the innovation.

More recently, a more comprehensive and explanatory model to predict technology acceptance within firms has arisen: the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Thong, & Xu, 2012). This model consolidates the previous Technology Acceptance Model-related research and provides a solid foundation for researchers to apply it to recent phenomena like internet banking, digital commerce, online learning, and behavior (Williams, Rana, & Dwivedi, 2015). This model was later extended and is commonly referred to as the UTAUT2. It shifts the main focus from interorganizational adoption to end-user consumer adoption, which is contextualized in a multitude of consumption scenarios. This extension allows the UTAUT2 to be applied to a broader set of consumer goods and incorporates hedonic motivation and price/value relationship, which marketers must conceptualize when trying to understand end-consumer adoption and usage (Venkatesh et al., 2012).

However, Williams et al. (2015) has suggested there is still a tendency, or preference, for many authors to conduct TAM-based studies because of its widespread use in previous studies and a certain level of maturity. No doubt the UTAUT2 model was evolutionary in nature, morphing from and extending the Theory of Reasoned Action, Theory of Planned Behavior, and Technology Acceptance Model, but the UTAUT2 is criticized for its lack of consideration of important variables like privacy and trust. This research has kept this absence of variables in mind, and because of privacy and trust concerns related to providing and sharing data in recent years (Hoy, 2018; Jones, 2018), this research intends to fill this significant research gap on AI's adoption and use.

To integrate the concepts of privacy and trust for modelling and to theorize about them to predict consumer behavior, one must first define the concepts. From a general consumer's perspective, there seems to be a general lack of awareness of and trust toward AI. From a conceptual standpoint, depending on the user's knowledge and experience, trust can be seen in two ways in this context: it can be defined as (a) willfully placing confidence in a party while providing personal information or (b) willfully making oneself vulnerable while sharing personal information (Lee, 2005). The consumer's self-view hinges on factors like the provider's reputation, initial trust, and the user's preferences and experience and continued trust. For example, in the case of Siri, consumers must feel comfortable providing information to the Apple corporation. Based on consumers' belief in the firm's good intentions and their experience of its past behavior, they are likely to put their trust in a new product/technology like Siri because it comes from Apple.

Moreover, consumer satisfaction with initial use prompts continued product/technology trust. Siau and Wang (2018) found consumers who initially use a product/new technology without incident are likely to continue to use and trust the product/technology.

Similarly, individuals' subjective beliefs play a part in perceived privacy risk. Although individuals must accept some level of risk when sharing their personal information, many consumers do not clearly understand what personal information companies collect and how they use it. Considering this, Pavlou and Gefern (2004) defined perceived privacy risk as one's subjective belief there is some probability of suffering a loss in pursuit of a desired outcome; in this context, these are product-related benefits.

As mentioned in the introduction, trust has been identified as essential for effective functioning of relationships in marketing (Sekhon et al., 2014). Most definitions of trust emphasize a perception of risk that is dependent on another party's actions (Hu, Wu, Wu, & Zhang, 2010; Luo, Li, Zhang, & Shim, 2010; Pavlou, 2003). In a product-consumer or buyer–seller relationship, consumers evaluate perceived risk, and then, their perceptions of the seller's/vendor's integrity are based on how the other party follows a set of accepted standards or principles (McKnight & Chervany, 2001). Because technology-mediated products are more available and used in the marketplace, the issue of trust has gained a new level of importance. However, consumer trust has not been fully integrated into privacy issues in the current literature (Miltgen & Smith, 2015). As consumers simultaneously develop trust and privacy beliefs, these two concepts should be studied together with other antecedents to make it possible to conceptualize consumer behavior (Pappas, 2018). This has been the approach in this study: trust has been studied along with other antecedents, like consumer interaction and novelty value.

Interestingly, some research quite rightly has taken into account e-commerce adoption (e.g., Pavlou, 2003) using the technology acceptance model. Research like this can motivate other new technological product adoption that may be driven by AI. Lack of trust, fear of monetary loss, and risk of data falling into some unintended hands (Pavlou, 2003) are all findings from e-commerce-adoption-related research that can be extrapolated for inspiration and interpretation from the AI context.

Although Gefen, Karahanna, and Straub's (2003) research on online shoppers was presented a while ago, it still provides an interesting set of insights and implications for products in the category of intelligent virtual assistants. Gefen et al. found when consumers believe vendors' intentions are benevolent and they have nothing to gain from cheating, consumers show a much higher level of trust. We can extend this finding on online shoppers to social media users. As an example, when Facebook came under attack in 2018 for its data breach, users did not anticipate trust being an issue because Facebook is a social media platform used for mostly non-commercial activity and people to enjoy innocuous fun.

Technology use has evolved since the studies previously mentioned took place. In terms of technological and social complexity, current intelligent virtual assistants have more advanced capabilities. Despite this, more recent studies on new mobile education platforms (e.g., Briz-Ponce, Pereira, Carvalho, Juanes-Méndez, & García-Peñalvo, 2017) identify the same issues of trust and privacy concerns in sectors like online education. So, for AI-mediated products like Siri, this is currently equally relevant despite our talking about more-advanced technology.

Perceived privacy risk and trust are critical factors in consumer behavior. Therefore, when assessing adoption and usage of information technology, they are both relevant to sharing sensitive personal information. Because AI is a recent, emerging, and sophisticated technology, we can understandably assume the average individual may not properly understand how the technology works; this puts the consumer in the precarious situation of blindly trusting a provider. This phenomenon has been confirmed: recent studies have found lack of trust and understanding actually slows new technology adoption (HSBC, 2018). Thus, intelligent voice assistant adoption can be understood better with this knowledge and in this context.

In addition to consumers grappling with trust and privacy issues in relation to these technologies, complexity in governance of these technologies from regulatory bodies intensifies the problem. Lohr (2019) acknowledged it is a struggle for policymakers, who are without a working knowledge of how AI is developed, to create effective rules and regulations to protect individuals from the potential misuse of personal information.

Current data show uptake of intelligent voice assistants is modest compared to smart phones (Kinsella, 2018). Some studies in the U.S. market have shown how millennials (18–24-year-olds) are the prime users of products like intelligent virtual assistants; however, the slightly higher age group (25–49-year-olds) are the heavy users of products like Siri (PwC, 2018).

Moreover, a well-adopted technology is more likely to make consumers brand loyal. Hence, a product's novelty value is not good enough: consumers must engage and interact with the product to feel that they are using the technology to the fullest extent (Petrock, 2019). In fact, usage has also been an issue because some studies have found intelligent voice assistants have only been used primarily for basic tasks, browsing, and listening to music. Therefore, attracting consumers via novelty value and then keeping them with improved and regular interactions are the keys to developing brand loyalty. This led to incorporating both of these as useful antecedents in the study.

Based on our discussion, a conceptual model (Fig. 1) was developed for this study. It contains the four elements investigated: trust, interaction, perceived risk, and novelty value.

Based on the conceptual model, four hypotheses were developed for testing (Table 1).

Table 1
Hypotheses Tested.

Hypotheses	Descriptions
H1	Trust of Siri has a significantly positive influence on brand loyalty.
H2	Interactions with Siri have a significantly positive influence on brand loyalty.
H3	Higher level of perceived risk will be associated with lower level of brand loyalty.
H4	Novelty value of Siri has a significantly positive influence on brand loyalty.

3. Research method

3.1. Participants and procedures

In this study, 700 participants made up the initial sample size. 12 incomplete responses and 13 responses that failed the attention check were deleted after a review, leaving the final sample size of 675. The sample size is adequate because it exceeds the recommended sample size of 100 (Hair, Black, Babin, & Anderson, 2010). Table 2 represents the descriptive statistics of the respondents. Only respondents who use an

Table 2
Descriptive Statistics.

Variable Definition	Frequency	Percent
Gender		
Male	268	39.70%
Female	407	60.30%
Age Range		
18–24	88	13.05%
25–34	273	40.44%
35–44	163	24.15%
45–54	84	12.44%
55–64	47	6.96%
65–74	20	2.96%
Education Level		
High school	103	15.26%
College/Associate Degree	130	19.26%
Bachelor's Degree	317	46.96%
Master's Degree	108	16.00%
Doctoral Degree	17	2.52%
Employment Status		
Full-time	486	72.00%
Part-time	103	15.26%
Retired	20	2.96%
Homemaker	33	4.89%
Unemployed	33	4.89%

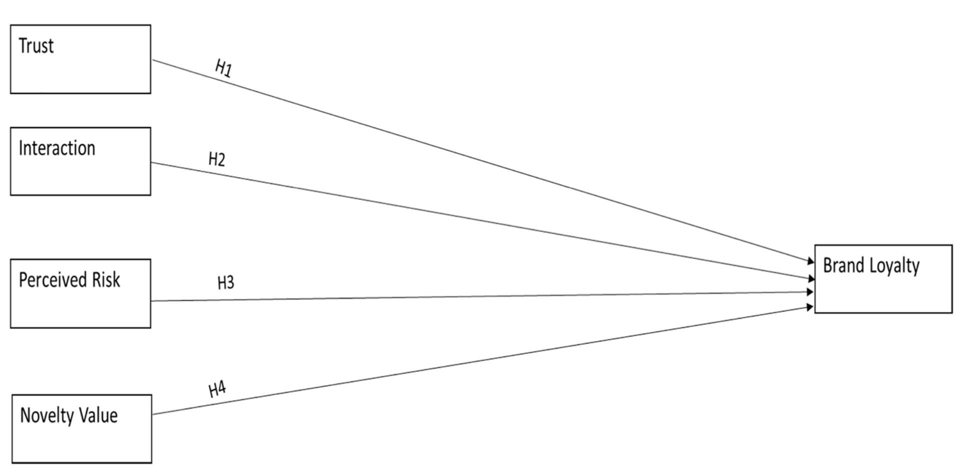

Fig. 1. Conceptual model.

Journal of Business Research 131 (2021) 591–597

Apple iPhone participated in this survey, which allowed us to investigate brand loyalty for Apple and capture information related to use of voice-assisted AI, like Siri, on their iPhones. We paid, on average, USD 1.50 per survey.

A convenience non-probability sampling technique was used because it seemed the most practical approach and is the most frequent method scholars use (Churchill & Iacobucci, 2009). Screening questions were used to determine whether the respondents used the voice-assisted artificial intelligence platform Siri on their iPhones. Then, the respondents answered questions related to their demographic information. The questions that followed related to trust, interaction, perceived risk, novelty value, brand loyalty, brand involvement, and consumer innovativeness. Each respondent took on average eight to ten minutes to complete the survey.

Data were collected using the MTurk platform. In recent studies, MTurk has been used extensively and considered a reliable and valid psychological data source (Buhrmester, Kwang, & Gosling, 2011; Hasan, Jha, & Liu, 2018; Paolacci, Chandler, & Ipeirotis, 2010). MTurk allowed us to capture wide and varied demographic and geographic data (Berinsky, Huber, & Lenz, 2011; Buhrmester et al., 2011). Specifically, it enabled us to collect data from countries like the United States, United Kingdom, Canada, India, and Turkey.

3.2. Measures

A 7-point Likert scale was used for most of this study's scales. The 7-point Likert scale captures greater variation compared to the 5-point Likert scale (Finstad, 2010). Most of the items were adapted from well-established sources, which ensured the reliability and validity of the measures. The items of each construct and their relevant sources are presented in Table 3.

Table 3
Constructs and Their Sources.

Constructs and Items	Sources
Trust 1. I believe Siri acts in my best interest. 2. I expect Siri to be sincere and genuine. 3. I believe Siri performs its roles very well.	Kääriä (2017)
Interactions 1. I can easily interact with Siri. 2. I can easily talk with Siri. 3. I can easily chat with Siri. 4. I can easily navigate using Siri.	Siddike, Spohrer, Demirkan, & Kohda (2018)
Novelty Value (NOV) 1. Using Siri is a unique experience. 2. Using Siri is a once-in-a-lifetime experience. 3. Using Siri is an educational experience. 4. The experience of using Siri satisfies my curiosity. 5. Using Siri provides an authentic/genuine experience.	Prebensen and Xie (2017)
Consumer innovativeness 1. If I heard about new information technology, I would look for ways to experiment with it. 2. Among my peers, I am usually the first to explore new information technologies. 3. I like to experiment with new information technologies. 4. I get a kick out of using new high-tech services before most other people know they exist. 5. It is cool to be the first to own new high-tech services. 6. Being the first to use new high-tech services is very important to me.	Zhang, Lu, & Kizildag (2017)
Brand involvement 1. Important _____Unimportant* 2. Boring _______Interesting 3. Relevant ______Irrelevant* 4. Exciting ______Unexciting* 5. Means nothing ___Means a lot to me 6. Appealing ______Unappealing* 7. Fascinating _____Mundane* 8. Worthless ______Valuable 9. Involving ______Uninvolving* 10. Not needed _____Needed	Zaichkowsky (1994)
Brand loyalty 1. I will buy the Apple brand the next time I buy any technology. 2. I intend to keep purchasing the Apple brand. 3. I am committed to the Apple brand. 4. I would be willing to pay higher price for the Apple brand over other brands.	Jacoby & Chestnut (1978)
Perceived Risk 1. It is risky to provide personal information to Siri. 2. There will be much uncertainty associated with providing personal information to Siri. 3. There will be much potential loss associated with providing personal information to Siri.	Zhou (2011)

3.3. Statistical analysis

Partial Least Squares-based (PLS-based) Structural Equation Modeling (SEM) was used to assess the measurement model and to ensure the reliability and validity of constructs and items.

PLS-SEM was appropriate for this study because it facilitated investigating the phenomenon in its early stage of development (Fornell & Bookstein, 1982). Also, a multivariate-normal distribution is not required for PLS-SEM (Albert & Merunka, 2013).

4. Results

4.1. Measurement model

In this study, the reliability and validity of each construct was tested using SmartPLS 3.0, and the measurement model was tested by running a bootstrapping sample of 5000. Therefore, convergent validity, reliability, and validity were assessed for each construct. Confirmatory factor analysis (CFA) was conducted to evaluate the convergent validity of each construct. Column 3 of Table 4 (Factor Loading [>0.7]) displays the results and shows all items loaded properly within their relevant theoretical construct. The Cronbach's alpha and composite reliability of each reflective construct were also assessed and presented in Table 4, and it appears the Cronbach's alphas and composite reliabilities were greater than the recommended threshold of 0.70 (Chin, 1998). Next, we calculated the discriminant validity of the measurement model; it is shown in Table 5, where the diagonal numbers represent square roots of average variance extracted (AVE), and the off-diagonal numbers represent the interconstruct correlations. It appears from the results that the square root of AVE is greater than the interconstruct correlations, providing sufficient evidence of appropriate discriminant validity (Lowry & Gaskin, 2014).

4.2. Structural model and analysis

We ran a bootstrapping sample of 5000 to test the structural model for this study (see the results in Fig. 2). Path coefficients of this figure demonstrate the relationship strength between dependent and independent constructs, and the R-squared values represent the variance explained by the study's independent constructs.

From Fig. 2, it appears that trust towards Siri has a significant positive influence on brand loyalty for Apple ($ß = 0.062$, $p < 0.1$), thus supporting hypothesis H1. Interactions with Siri was found to have significant positive influence on brand loyalty for Apple ($ß = 0.106$, $p < 0.05$), thus supporting hypothesis H2. The influence of perceived risk of using Siri has a significant negative influence on brand loyalty for Apple ($ß = -0.061$, $p < 0.05$), thus supporting hypothesis H3. The negative

Table 4
Results of the Measurement Model.

Constructs	Items	Factor Loading (>0.7)	Mean	Standard Deviation	Cronbach's alpha	Composite Reliability	AVE
Brand Involvement	BINV 1	0.819	2.370	1.043	0.929	0.940	0.612
	BINV 2	0.762					
	BINV 3	0.757					
	BINV 4	0.831					
	BINV 5	0.711					
	BINV 6	0.820					
	BINV 7	0.788					
	BINV 8	0.761					
	BINV 9	0.809					
	BINV 10	0.757					
Brand Loyalty towards Apple	BLYL 1	0.89	5.434	1.281	0.906	0.934	0.780
	BLYL 2	0.887					
	BLYL 3	0.901					
	BLYL 4	0.854					
Consumer Innovativeness	CINV 1	0.882	4.520	1.488	0.934	0.948	0.753
	CINV 2	0.891					
	CINV 3	0.846					
	CINV 4	0.870					
	CINV 5	0.866					
	CINV 6	0.852					
Interaction with Siri	ITRT 1	0.906	5.222	1.345	0.916	0.941	0.799
	ITRT 2	0.916					
	ITRT 3	0.898					
	ITRT 4	0.855					
Novelty Value	NVLT 1	0.817	4.098	1.343	0.868	0.904	0.655
	NVLT 2	0.689					
	NVLT 3	0.814					
	NVLT 4	0.848					
	NVLT 5	0.867					
Perceived Risk of using Siri	PCRK 1	0.938	3.944	1.653	0.931	0.956	0.879
	PCRK 2	0.938					
	PCRK 3	0.936					
Trust towards Siri	TRST 1	0.912	4.740	1.275	0.897	0.936	0.829
	TRST 2	0.908					
	TRST 3	0.911					

Table 5
Discriminant Validity of the Measurement Model.

Model Constructs	BINV	BLYL	CINV	ITRT	NVLT	PCRK	TRST
Brand Involvement (BINV)	**0.782**						
Brand Loyalty (BLYL)	−0.654	**0.883**					
Consumer Innovativeness (CINV)	−0.255	0.242	**0.868**				
Interaction (ITRT)	−0.318	0.345	0.358	**0.894**			
Novelty Value (NVLT)	−0.295	0.306	0.513	0.509	**0.809**		
Perceived Risk (PCRK)	0.325	−0.286	−0.264	−0.218	−0.152	**0.937**	
Trust (TRST)	−0.377	0.373	0.467	0.451	0.594	−0.289	**0.911**

influence of perceived risk of using Siri was found to be moderated by employment in such a way that the negative influence is greater for unemployed consumers (ß = −0.069, $p < 0.05$). Novelty value of using Siri was found to have a significant positive influence on brand loyalty for Apple (ß = 0.057, $p < 0.1$), thus supporting hypothesis H4. The influence of novelty value of using Siri was found to be moderated by brand involvement and consumer innovativeness in such a way that the influence was found to be greater for consumers who are less involved with the brand ((ß = 0.157, $p < 0.05$) and who are more innovative (ß = 0.106, $p < 0.05$).

We also see that the R-square value of brand loyalty is 48.90%, which means that a 48.90% variance of brand loyalty is explained by trust, interaction, perceived risk, and novelty value in relation to the use of Siri.

5. Discussion and conclusion

Almost all major mobile phone players have introduced intelligent voice assistants to the market (Easwara Moorthy & Vu, 2015). Therefore, this research has wider implications for consumers and stakeholders as the future of responsible AI in society is debated. Application of AI is being extended to various home appliances and within the automobile industry; this, again, expands the relevance of such research (Knight, 2012). Privacy concerns is a negative issue in this discussion; however, AI that reduces barriers to using technology can improve the adoption of useful technology by various groups of people (e.g., low-literacy users, dementia patients, etc.) who may in fact need these services more than others (Hoy, 2018).

Millennials are the primary driving force behind the mainstream adoption of intelligent virtual assistants, like Siri (PwC, 2018); however, although that younger group (18–24-year-olds) are adopting intelligent voice technology, current 25–49-year-olds are heavy users of it (PwC,

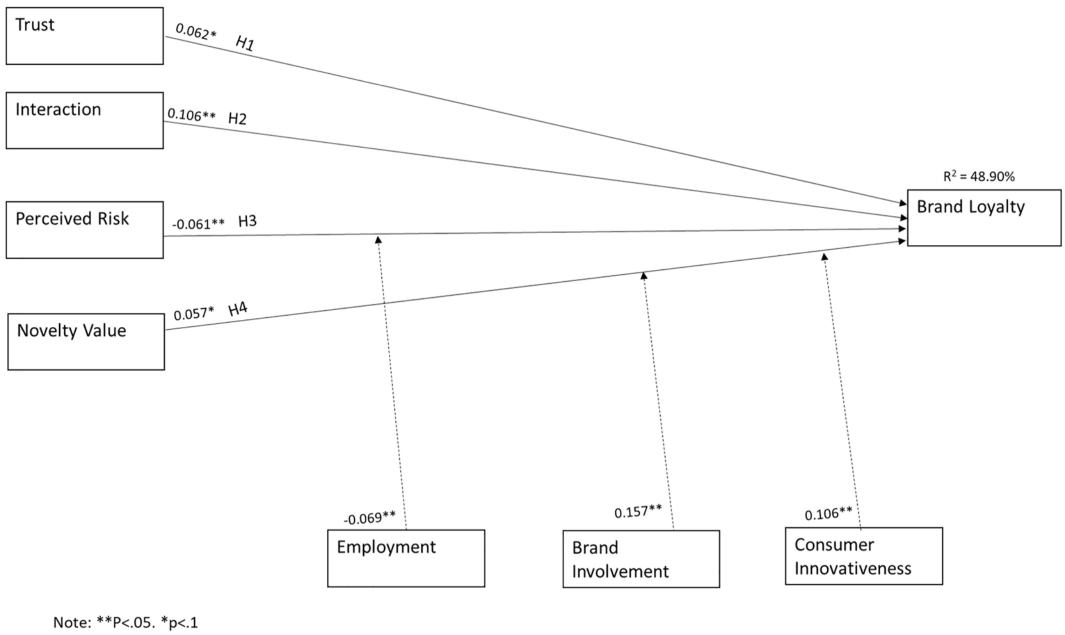

Fig. 2. Results of the proposed model.

2018). The novelty value entices the millennials, but the challenge lies in building regular interactions and thus overcoming perceived risk of privacy. It also raises some interesting questions about brand loyalty. Employability status was identified in this primary research, and that may also contribute to this understanding.

Moreover, 2018 figures show in the United States, just over half of the over 250-million smartphone users have used an intelligent voice assistant at some time (Kinsella, 2018). It is obvious that barriers like perceived risk are acting as a hindrance and keeping this adoption rate relatively low. Also, the extent and breadth of intelligent voice assistant use is not encouraging. Consumers are mainly using them to ask basic questions, search on browsers, and listen to music (Petrock, 2019). Our research has shown the way to engage loyal brand customers who would use an intelligent voice assistant, like Siri, to the fullest consumer advantage while also opening up new product development opportunities for marketers is to encourage greater brand involvement and consumer innovativeness.

A key issue this study reinforces is in the process of accruing greater benefits for society, there will be an absence of transparency and regulations surrounding recording and transmitting audio samples, even when the virtual assistant is in dormant mode. Although some companies have issued public apologies for breaching users' privacy, consumers may revisit and rethink using such software and devices (Haselton, 2019).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ajzen, I. (1991). The theory of planned behavior. Special issue: Theories of cognitive self-regulation. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.
Albert, N., & Merunka, D. (2013). The role of brand love in consumer-brand relationships. *Journal of Consumer Marketing, 30*(3), 258–266. https://doi.org/10.1108/07363761311328928.
Arts, J. W. C., Frambach, R. T., & Bijmolt, T. H. A. (2011). Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behaviour. *International Journal of Research in Marketing, 28*(2), 134–144.
Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2011). Replication data for: Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. [IQSS Dataverse Network]. Retrieved from http://hdl.handle.net/1902.1/17220.
Briz-Ponce, L., Pereira, A., Carvalho, L., Juanes-Méndez, J. A., & García-Peñalvo, F. J. (2017). Learning with mobile technologies–Students' behavior. *Computers in Human Behavior, 72*(July), 612–620. https://doi.org/10.1016/j.chb.2016.05.027.
Buhrmester, M. D., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science, 6*(1), 3–5.
Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295–336.
Chung, H., Iorga, M., Vaos, J., & Lee, S. (2017). Alexa, can I trust you? *Computer, 50*(9), 100–104. https://doi.org/10.1109/MC.2017.3571053.
Churchill, G., & Iacobucci, D. (2009). *Marketing research: Methodological foundations* (10th ed.). Nashville, TN: South-Western College Publishing.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.
Davis, F. D. (1993). User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *International Journal of Man Machine Studies, 38*(3), 475–487.
Easwara Moorthy, A., & Vu, K.-P.-L. (2015). Privacy concerns for use of voice activated personal assistant in the public space. *International Journal of Human-Computer Interaction, 31*(4), 307–335. https://doi.org/10.1080/10447318.2014.986642.
Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research, 19*(4), 440–452.
Finstad, K. (2010). The usability metric for user experience. *Interacting with Computers, 22*(5), 323–327.
Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behaviour: An introduction to theory and research*. Reading, Massachusetts: Addison-Wesley.
Gatignon, H., & Robertson, T. S. (1985). A propositional inventory for new diffusion research. *Journal of Consumer Research, 11*(4), 849–867.
Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90.
Hasan, M. R., Jha, A. K., & Liu, Y. (2018). Excessive use of online video streaming services: Impact of recommender system use, psychological factors, and motives. *Computers in Human Behavior, 80*(March), 220–228. https://doi.org/10.1016/j.chb.2017.11.020.
Haselton, T. (2019). Apple apologizes for listening to Siri conversations. CNBC. Retrieved 20/10/2019 from https://www.cnbc.com/2019/08/28/apple-apologizes-for-listening-to-siri-conversations.html.
Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Essex, UK: Pearson.
Hoeffler, S. (2003). Measuring preferences for really new products. *Journal of Marketing Research, 40*(4), 406–420.
Hoy, M. (2018). Alexa, Siri, Cortana, and more: An introduction to voice assistants. *Medical Reference Services Quarterly, 37*(1), 81–88.
HSBC (2018). Trust in technology. Retrieved from https://www.hsbc.com/-/files/hsbc/media/media-release/2017/170609-updated-trust-in-technology-final-report.pdf.
Hu, X., Wu, G., Wu, Y., & Zhang, H. (2010). The effects of Web assurance seals on consumers' initial trust in an online vendor: A functional perspective. *Decision Support Systems, 48*(2), 407–418.

Jacoby, J., & Chestnut, R. W. (1978). *Brand loyalty: Measurement and management*. New York, NY: John Wiley & Sons.
Jones, V. (2018). Voice-activated change: Marketing in the age of artificial intelligence and virtual assistants. *Journal of Brand Strategy, 7*(3), 233–245.
Kääriä, A. (2017). Technology acceptance of voice assistants: Anthropomorphism as factor (Master's thesis, University of Jyväskylä). Available from https://jyx.jyu.fi/bitstream/handle/123456789/54612/URN%3ANBN%3Afi%3Ajyu-201706202988.pdf?sequence=1.
Kinsella, B. (2018). Over half of smartphone owners use voice assistants, Siri leads the pack. Voicebot.ai. Retrieved 03/05/19 from https://voicebot.ai/2018/04/03/over-half-of-smartphone-owners-use-voice-assistants-siri-leads-the-pack/.
Knight, W. (2012). Where speech recognition is going. MIT Technology Review. Retrieved March 9th, 2019 from https://www.technologyreview.com/2012/05/29/255893/where-speech-recognition-is-going/.
Lee, T. (2005). The impact of perceptions of interactivity on customer trust and transaction intentions in mobile commerce. *Journal of Electronic Commerce Research, 6*(3), 165–180.
Lohr, S. (2019). How do you govern machines that can learn? Policymakers are trying to figure that out. The New York Times. Retrieved 01/06/20 from https://www.nytimes.com/2019/01/20/technology/artificial-intelligence-policy-world.html.
Lombardi, R., Giudice, D., Caputo, A., Evangelista, F., & Russo, G. (2016). Governance and assessment insights in information technology: The Val IT model. *Journal of the Knowledge Economy, 7*(1), 292–308.
Lombardi, R., Rossi, N., & Russo, G. (2012). Innovative forms of accountability in the public administration: Sustainability reports. *Journal of US-China Public Administration, 9*(10), 1107–1121.
Lowe, B., & Alpert, F. (2015). Forecasting consumer perception of innovativeness. *Technovation, 45–46*(November–December), 1–14. https://doi.org/10.1016/j.technovation.2015.02.001.
Lowry, P. B., & Gaskin, J. (2014). Partial Least Squares (PLS) Structural Equation Modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication, 57*(2), 123–146.
Luo, X., Li, H., Zhang, J., & Shim, J. P. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision Support Systems, 49*(2), 222–234.
McKnight, D. H., & Chervany, N. L. (2001). What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International Journal of Electronic Commerce, 6*(2), 35–59.
Miltgen, C. L., & Smith, H. J. (2015). Exploring information privacy regulation, risks, trust, and behavior. *Information & Management, 52*(6), 741–759.
Morgan, B. (2018). How Amazon has reorganized around artificial intelligence and machine learning. Forbes. Retrieved from https://www.forbes.com/sites/blakemorgan/2018/07/16/how-amazonhas-re-organized-around-artificial-intelligence-and-machine-learning/#8ec10ac73618.
Norvig, P. (2012). Artificial intelligence: Early ambitions. *New Scientist, 216*(2889), ii–iii. https://doi.org/10.1016/s0262-4079(12)62783-3.
Ostlund, L. E. (1974). Perceived innovation attributes as predictors of innovativeness. *Journal of Consumer Research, 1*(2), 23–29.
Paolacci, G., Chandler, J., & Ipeirotis, P. (2010). Running experiments using Amazon Mechanical Turk. *Judgment and Decision Making, 5*(5), 411–419.
Pappas, I. O. (2018). User experience in personalized online shopping: A fuzzy-set analysis. *European Journal of Marketing, 52*(7/8), 1679–1703.
Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134.
Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research, 15*(1), 37–59.
Petrock, V. (2019). US voice assistant users 2019: Who, what, when, where and why. eMarketer. Retrieved 03/08/19 from https://www.emarketer.com/content/us-voice-assistant-users-2019.
Prebensen, N. K., & Xie, J. (2017). Efficacy of co-creation and mastering on perceived value and satisfaction in tourists' consumption. Tourism Management, 60(June), 166–176. Doi: 10.1016/j.tourman.2016.12.001.
PwC (2018). Consumer Intelligence Series: Prepare for the voice revolution. Retrieved 03/05/19 from https://www.pwc.com/us/en/advisory-services/publications/consumer-intelligence-series/voice-assistants.pdf.
Rogers, E. M. (1962). *Diffusion of innovations* (1st ed.). New York, NY: Free Press.
Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.
Sekhon, H., Ennew, C., Kharouf, H., & Devlin, J. (2014). Trustworthiness and trust: Influences and implications. *Journal of Marketing Management, 30*(3–4), 409–430. https://doi.org/10.1080/0267257X.2013.842609.
Shams, S. M. R., & Solima, L. (2019). Big data management: Implications of dynamic capabilities and data incubator. *Management Decision, 57*(8), 2113–2123.
Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal, 31*(2), 47–53.
Siddike, M. A. K., Spohrer, J., Demirkan, H., & Kohda, Y. (2018). People's interactions with cognitive assistants for enhanced performances. In Proceedings of the 51st Hawaii International Conference on System Sciences (pp. 1640–1648). https://scholarspace.manoa.hawaii.edu/bitstream/10125/50092/paper0205.pdf.
Trequattrini, R., Shams, R., Lardo, A., & Lombardi, R. (2016). Risk of an epidemic impact when adopting the internet of things: The role of sector-based resistance. *Business Process Management Journal, 22*(2), 403–419.
Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. IEEE Transactions on Engineering Management, EM-29(1), 28–43. http://www.management.wharton.upenn.edu/klein/documents/Tornatzky_Klein_1982.pdf.
Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and user of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178.
Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management, 28*(3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088.
Zaichkowsky, J. L. (1994). The personal involvement inventory: Reduction, revision, and application to advertising. *Journal of Advertising, 23*(4), 59–70. https://doi.org/10.1080/00913367.1943.10673459.
Zhang, T., Lu, C., & Kizildag, M. (2017). Engaging Generation Y to co-create through mobile technology. *International Journal of Electronic Commerce, 21*(4), 489–516.
Zhou, T. (2011). The impact of privacy concern on user adoption of location-based services. *Industrial Management & Data Systems, 111*(2), 212–226.