Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research

Janin Karoli Hentzen, Arvid Hoffmann and Rebecca Dolan
Adelaide Business School, The University of Adelaide, Adelaide, Australia, and
Erol Pala
AUT Business School, Auckland University of Technology, Auckland, New Zealand

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Abstract

Purpose – The objective of this study is to provide a systematic review of the literature on artificial intelligence (AI) in customer-facing financial services, providing an overview of explored contexts and research foci, identifying gaps in the literature and setting a comprehensive agenda for future research.

Design/methodology/approach – Combining database (i.e. Scopus, Web of Science, EBSCO, ScienceDirect) and manual journal search, the authors identify 90 articles published in Australian Business Deans Council (ABDC) journals for investigation, using the TCCM (Theory, Context, Characteristics and Methodology) framework.

Findings – The results indicate a split between data-driven and theory-driven research, with most studies either adopting an experimental research design focused on testing the accuracy and performance of AI algorithms to assist with credit scoring or investigating AI consumer adoption behaviors in a banking context. The authors call for more research building overarching theories or extending existing theoretical perspectives, such as actor networks. More empirical research is required, especially focusing on consumers' financial behaviors as well as the role of regulation, ethics and policy concerned with AI in financial service contexts, such as insurance or pensions.

Research limitations/implications – The review focuses on AI in customer-facing financial services. Future work may want to investigate back-office and operations contexts.

Originality/value – The authors are the first to systematically synthesize the literature on the use of AI in customer-facing financial services, offering a valuable agenda for future research.

Keywords Systematic literature review, Artificial intelligence, Financial services, Bank marketing

Paper type Research paper

1. Introduction

Human intelligence refers to a person's ability to learn and adapt from their experience and environment (Schlinger, 2003). Components include reasoning, decision-making, learning, problem-solving and communicating (Russell and Norvig, 2010). While human intelligence continues to be a highly debated topic, nonhuman or artificial intelligence has intrigued many great minds over the past centuries, including philosophers, mathematicians, writers and scientists. Intelligent machines have ignited the search for answers as to what defines human intelligence and attempts to replicate and improve such intelligence. Despite the occasional conceptualizations of nonhuman intelligence throughout the centuries, scholars consider 1956 as the beginning of artificial intelligence as an academic research area. Specifically, it is all believed to have started with a conference at Dartmouth College in the USA (Haenlein and Kaplan, 2019).

Since then, artificial intelligence (hereafter: AI) research has undergone slow development, little research attention and low industry adoption. However, with recent advances in computational technology, Big Data and increased industry demand, AI is rapidly transforming customer experiences, organizations and industries (Xu *et al.*, 2020). While service industries are usually considered more difficult to automate due to the contextual

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understanding of communicational cues (i.e. nonverbal cues and human interaction), it is subject to radical technological transformation (Davenport *et al.*, 2020; Huang and Rust, 2018; van Doorn *et al.*, 2016). AI has the potential to alter healthcare services, retail and consumer services, communication and entertainment services, and financial services (Pemer, 2020; PWC, 2017; van Esch *et al.*, 2020).

Financial services are traditionally considered a high-involvement context, with the industry moving to the forefront of adopting new technologies, leading to the rapid development of "FinTech," including AI (Citi Group, 2018). For example, spending on AI by the financial service sector in the Asia Pacific is expected to reach US$ 4.29 bn in 2024 (Kapoor and Bisht, 2020). So far, AI is used in fraud detection, risk management and cybersecurity, chatbots, algorithmic trading, robo-advisory, credit scoring, asset and wealth management, as well as relationship management and regulation (Buchanan, 2019; Chan *et al.*, 2019; Deloitte, 2018). AI has thus become an important issue in financial service marketing, warranting a systematic review of the literature (Cubric, 2020). Such a review is indispensable for informing (future) empirical research, aiding policy makers and business practitioners and setting the foundation for theoretical conceptualizations (Snyder, 2019). The number of academic studies around AI and its applications in financial services (marketing) has risen significantly in the past five years. However, the expected rise in systematic literature reviews has not followed. Our study addresses this gap.

Similar to Payne *et al.* (2021a) and Fernandes and Oliveira (2021), we contend that the application of AI within the financial services context is diverse and includes a wide range of activities, including customer-facing applications, such as chatbots, and noncustomer-facing applications, such as auditing. We limit the scope of our review to customer-facing AI applications to match the readership of this journal and avoid our review becoming overly technically complex. Our study is motivated by several limitations of the existing literature. First, prior literature reviews typically focus on one specific aspect of financial services, such as credit scoring (e.g. Bhatore *et al.*, 2020; Dastile *et al.*, 2020) and blockchain technology (Ali *et al.*, 2020). Second, literature reviews that do have an expanded scope fail to adopt a systematic approach (e.g. Cavalcante *et al.*, 2016; Konigstorfer and Thalmann, 2020; Milana and Ashta, 2021). Against this backdrop, our systematic literature review complements and extends prior reviews by providing the first review of studies on artificial intelligence in customer-facing financial services and outlining future research directions to support the advancement of this research field. We employ the Theory, Context, Characteristics and Methodology (TCCM) framework (Paul and Rosado-Serrano, 2019), which has been argued to generate more informative, insightful and robust insights compared to other approaches (Paul and Criado, 2020). Specifically, our systematic literature review seeks to answer the following questions: What *theories* are applied to study the impact of AI on customer-facing financial services? In what *context* (e.g. type of financial service) did prior investigations take place? What *characteristics* (e.g. variables) are studied in prior research? What are the most frequently applied research *methods* in previous work? And, finally, what are particularly promising opportunities for *future research* that arise from a systematic review of the extant literature?

We contribute to the literature on the intersection of AI and financial services marketing in multiple ways. First, our study provides a comprehensive overview of the current state of AI in financial services research. In total, we review 90 articles pertaining to both empirical and theoretical characteristics, of which some have not been considered previously. Based on the TCCM framework, our review finds that most of the included studies follow a data-driven approach, with less than half relying on theories to explain AI-related effects. Most research is set in developed countries and focuses on AI applications in banking and credit risk scoring, studied using quantitative methods, such as surveys or experiments. Our analysis of independent, dependent, mediating and moderating variables suggests that AI research has primarily studied consumer technology and service experience-related variables, whereas promising variables related to actor networks or consumer behavior have received only limited research attention to date.

Second, based on the insights gained from our literature review, we develop an agenda for future research, outlining topics and potential research questions based on the TCCM framework. We suggest future research to combine data- and theory-driven research and use diverse theoretical perspectives to better account for the broader impact of AI on the financial services ecosystem, including nonbanking contexts related to insurance and pensions. Finally, we call for future research to empirically investigate AI's ethical, legal and regulatory implications in financial services.

2. Research methodology

Systematic reviews seek to summarize research findings and general literature in a transparent, systematic and reproducible way (Davis *et al.*, 2014). While traditionally not overly prevalent, the number of systematic literature reviews in business journals is increasing. Select journals such as the *International Journal of Bank Marketing* (Fernández-Olit *et al.*, 2019; Kumar *et al.*, 2019), the *International Journal of Consumer Studies* (Paul *et al.*, 2021a) and the *Journal of Business Research* (Mandler *et al.*, 2021; Paul *et al.*, 2021b) have recognized the value of systematic literature reviews for the development of the field and are increasingly publishing these types of articles.

2.1 Inclusion and exclusion criteria

As mentioned, we limit the scope of our review to AI in customer-facing financial services. The term AI is often interchangeably used with machine learning (ML) or deep learning (DL), but they are not the same (Ashta and Herrmann, 2021). AI is considered an umbrella term, encompassing both ML and DL, which differ theoretically and in application. While AI is described as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein and Kaplan, 2019, p. 5), ML "is a subset of AI, which uses statistical tools to learn from data and then applies algorithms to solve problems" (Ashta and Herrmann, 2021, p. 212). ML can take data and algorithms and apply these to new scenarios without being programmed directly to do so (Buchanan, 2019). On the other hand, DL aims to understand underlying principles and patterns of data, which it can then combine with algorithms to learn on its own. ML classifications include supervised, semi-supervised, unsupervised and reinforcement learning, and the algorithms can be categorized into classifiers, regression and clustering (Campesato, 2020). While we did include articles applying ML, we did not include ML, DL or specific algorithms (e.g. neural networks, support vector machines) as separate search terms given the scope of our literature review. Table 1 summarizes the inclusion and exclusion criteria we used.

2.2 Search strategy

Following the prior literature (e.g. Chen *et al.*, 2021; Mandler *et al.*, 2021; Payne *et al.*, 2021a), our data search and collection comprise two phases: (1) an electronic database search and (2) a manual Google Scholar citation and key journal search. For the electronic database search, we identify relevant keywords based on the authors' expertise and agreement. We then enter the resulting search string, consisting of keyword combinations using Boolean operators "AND" and "OR" (see Table 1), into four electronic databases: Scopus, Web of Science, EBSCO and Science Direct. We restrict our search to the papers' abstract, title or keywords and limit it to

1	Scopus	"AI" OR "artificial intelligence" AND "financial service" OR "financial services marketing" OR "banking" OR "loan" OR "credit" OR "financial advice" OR "financial planning" OR "wealth management" OR "investment" OR "retirement" AND "customer" OR "consumer"	Jun-21	722
			Oct-21	57[a]
2	WoS		Jun-21	374
			Oct-21	365[a]
3	EBSCO		Jun-21	389
4	ScienceDirect		Jun-21	97
			Total	2,004

Inclusion criteria	
Topic	Accepted articles need to investigate artificial intelligence in the context of customer-facing financial services (B2C) Authors must be able to contextually place research articles through title and abstract review, that is, financial services and artificial intelligence or related terminology must be mentioned in either article title, abstract or keywords
Document type	Empirical and conceptual articles published in peer-reviewed journals As suggested by Paul and Criado (2020), Paul *et al.* (2021b), articles must be published in journals ranked on the 2019 ABDC list
Language	All included articles are published in English
Exclusion criteria	
Topic	Articles focused on a business-to-business (B2B) context such as corporate bankruptcy prediction or auditing
Document type	Books, book chapters and conference papers are excluded from the review
Language	Articles written in a language other than English

Note(s): [a] = A second search was conducted in October 2021 to account for articles published during the journal review process between the first search in June 2021 and October 2021

Table 1.
Search strategy and criteria

only include academic journal articles published in peer-reviewed journals and written in English.

The first phase of the data collection process yields 1,582 articles. After removing duplicates, this becomes 870 articles. We then proceed with a journal quality check, only keeping articles in journals ranked by the ABDC 2019 Journal Quality List, resulting in 361 articles to be included in an initial title and abstract review. All authors then commence reading the title and abstracts of these articles, after which 65 articles are selected for further investigation (98% author agreement). The authors then progress with the second phase of the data collection process, which includes a manual search checking the Google Scholar citations of the selected articles, resulting in an additional 13 articles to be included. In the third phase of the data collection process, the authors manually searched the archives of six leading service research journals (i.e. *Journal of Service Management, Journal of Service Research, Journal of Services Marketing, Journal of Service Theory and Practice, Service Science* and *Service Industries Journal*), five leading marketing journals (i.e. *Journal of Marketing, Journal of Marketing Research, Marketing Science, Journal of the Academy of Marketing Science* and *International Journal of Research in Marketing*) as well as the *International Journal of Bank Marketing* to acknowledge our target readership. The manual journal search results in an additional seven articles, bringing the total number to 85. To account for articles published during the journal review process after the first data collection in June 2021, a second search was conducted in October 2021. While the second search applies the same inclusion and exclusion criteria, the authors limited the search to articles published in 2021. Five additional articles were identified, bringing the total number of articles included in the review to 90 (see Appendix 1), which is within the recommended range (Paul and Criado, 2020). Figure 1 visualizes how we arrived from the initial 2,004 articles to the final 90 articles included in the review.

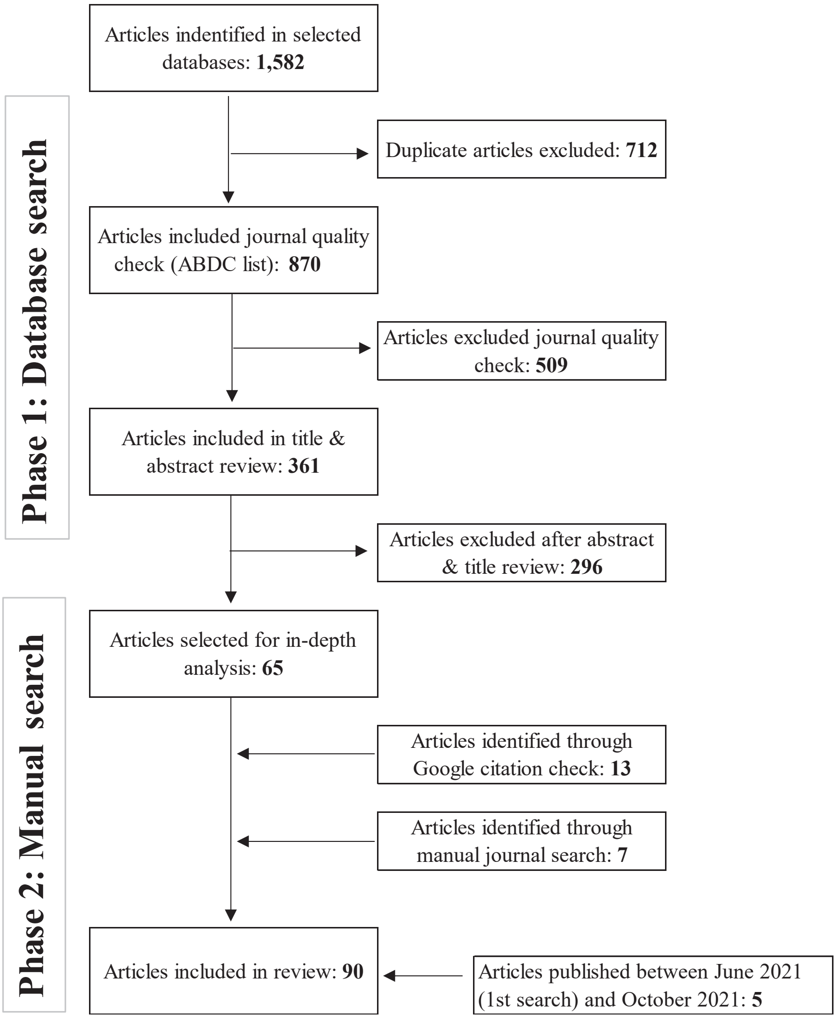

Figure 1. Overview of systematic review process

3. Publication trends

3.1 Year and country of publication

We organize the articles based on year and country of publication. Figure 2 details the distribution of the studies' publication dates, spanning from 1996 to 2021. Since 2016–2017, the domain has gained increasing momentum, culminating in 25 new publications in the year 2021.

Due to the nature of the studies, we considered both country of analysis and the source of data. Numerous studies conducting experiments or simulations utilize publicly available data from specified countries (i.e. Zhang *et al.*, 2019). Some studies cover multiple countries of analysis, which leads to the total count exceeding the number of studies. As indicated in Table 2, most studies are based on data from North America ($n = 17$), which includes the USA and Canada, as well as DACH countries ($n = 16$), which include Germany, Switzerland and Austria. However, most of the latter studies use German data ($n = 14$). These are closely

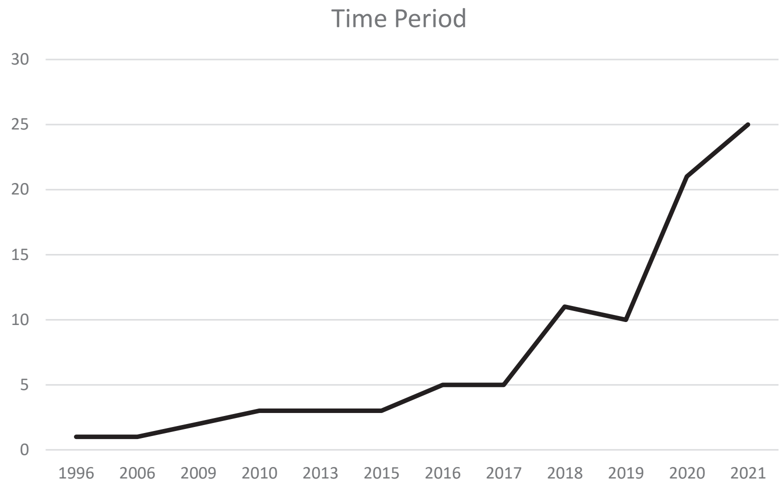

Figure 2.
Time frame covered by systematic review and # of articles published

followed by studies conducted in East Asian countries (*n* = 13), including China, Taiwan, Japan and South Korea. Also represented are studies from the United Kingdom (*n* = 10), Mediterranean countries, such as Italy, Spain, Portugal and Malta (*n* = 8), and Australia (*n* = 8). Many Middle Eastern countries were present (*n* = 9), with most studies based on Iranian data (*n* = 4). Somewhat underrepresented were African (*n* = 4) and Latin American countries (*n* = 1). Numerous studies did not report a country of analysis (*n* = 18), partly due to these studies' conceptual nature (Payne *et al.*, 2021a).

It is not surprising that many studies focus on the USA and Germany, as both countries are at the forefront of AI-technology development and investment. While the USA invested US$ 18.2 bn into AI between 2012 and 2016 (Buchanan, 2019), Germany is set to spend €5 bn by 2025 (European Commission, 2020). Surprisingly, although China aims to become the world's primary AI innovation center, with estimated investments between $1.7 and $5.7 bn in 2018 (Acharya and Arnold, 2019), comparatively few articles include Chinese data. Finally, although some studies focused on the effectiveness of AI in enhancing financial inclusion, only a few articles are set within the context of developing nations (e.g. Abdulquadri *et al.*, 2021; Bhatia *et al.*, 2020).

3.2 Publication outlet

The 90 articles included in the review span over 60 separate journals from various disciplines, including marketing, management, finance, business, economics, law, social sciences and information systems management. Table 3 provides an overview of the 13 journals with the most publications, showing that articles on AI in customer-facing financial services are yet to find a footing in top-tier journals. That is, 39% (*n* = 35) of articles are published in C and 23% (*n* = 21) in B-ranked journals, compared to only 9% (*n* = 8) in A* and 29% (*n* = 26) in A-ranked journals.

3.3 Keyword analysis

Keywords aim to provide vital insights into the content of a particular journal article. Analyzing authors' specified keywords may shed light on the dominant focus of an area of research while simultaneously confirming the visibility of select articles. We provide a visualized summary of the most frequently used keywords employed in the sample articles in Figure 3. The most noticeable keywords (e.g. *artificial intelligence, financial** and *service*)

Country	#	%	Exemplar studies
Africa			
Egypt	1	1%	Abdelazim and Wahba (2006)*
Nigeria	2	2%	Abdulquadri *et al.* (2021), Mogaji *et al.* (2021)
Tunisia	1	1%	Khemakhem *et al.* (2018)
Americas			
North America (USA and Canada)	17	19%	Abdelazim and Wahba (2006), Ashta and Herrmann (2021), Bai (2021), Bejou *et al.* (1996), Belanche *et al.* (2019), Brenner and Meyll (2020), Flavián *et al.* (2021), Fulk *et al.* (2018), Lee and Shin (2020), Leung *et al.* (2009), Payne *et al.* (2021b), Payne *et al.* (2018), Ramanathan and Wechsler (2013), Shanmuganathan (2020), Tokic (2018), Tubadji *et al.* (2021)*, Zhang *et al.* (2021a)
Latin America (Brazil)	1	1%	Sun and Vasarhelyi (2018)
Asia and Oceania			
Australia	8	9%	Abellán and Castellano (2017), Ala'raj and Abbod (2016), Ashta and Herrmann (2021), Singh *et al.* (2021a)*, Tubadji *et al.* (2021)*, Zhang *et al.* (2019, 2021b)
East Asia (China, Taiwan, Japan and South Korea)	13	14%	Ala'raj and Abbod (2016)*, Ashta and Herrmann (2021)*, Guo (2020), Huang and Pan (2010), Jang *et al.* (2021), Xu *et al.* (2020), Yu *et al.* (2009)*, Zhang *et al.* (2019, 2021b)*
South Asia (India and Indonesia)	5	6%	Bhatia *et al.* (2020), Kaur *et al.* (2020), Mor and Gupta (2021), Philip *et al.* (2018), Rasiwala and Kohl (2021), Suhartanto *et al.* (2021)
Nondisclosed Asian country	1	1%	Luo *et al.* (2019)
Europe			
Benelux (Netherlands and Luxembourg)	6	7%	Correa Bahnsen *et al.* (2016)*, Henkel *et al.* (2020), Tubadji *et al.* (2021)*, van Thiel and van Raaij (2019)*
DACH countries (Germany, Austria and Switzerland)	16	18%	Abellán and Castellano (2017)*, Adam *et al.* (2020), Atwal and Bryson (2021), Correa Bahnsen *et al.* (2016)*, Hildebrand and Bergner (2020), Kraus and Feuerriegel (2017), Singh *et al.* (2021a)*, Trivedi (2019), Tubadji *et al.* (2021)*, Yu *et al.* (2009)*, Zhang *et al.* (2019, 2021b)*
Eastern Europe (Czech Republic, Poland and Romania)	7	8%	Abellán and Castellano (2017)*, Ala'raj and Abbod (2016)*, Iiie *et al.* (2017), Ładyżyński *et al.* (2019), Tubadji *et al.* (2021)*
EU (unspecified)	4	4%	Ashta and Herrmann (2021)*, Borgogno and Colangelo (2019), Kapsis (2020), Kruppa *et al.* (2013)
France	1	1%	Tubadji *et al.*, 2021*
Mediterranean countries (Italy, Malta, Spain and Portugal)	8	9%	Belanche *et al.* (2019)*, Castillo *et al.* (2020), Gallego-Gomez and De-Pablos-Heredero (2020), Lu *et al.* (2016), Paleologo *et al.* (2010), Tubadji *et al.*, 2021*
The United Kingdom	10	11%	Aggarwal (2021), Belanche *et al.* (2019)*, Chiu (2019), Lee (2020), Lui and Lamb (2018), Punniyamoorthy and Sridevi (2016), Ramanathan and Wechsler (2013)*, Tubadji *et al.*, 2021*, van Thiel and van Raaij (2019)*, Yu *et al.* (2009)*
Global	3	3%	Kumar and Balaramachandran (2018), Lightbourne (2017), Mhlanga (2021)
Middle East			
Armenia	1	1%	Baghdasaryan *et al.* (2021)
Iran	4	5%	Abellán and Castellano (2017)*, Ala'raj and Abbod (2016)*, Koutanaei *et al.* (2015), Zeinalizadeh *et al.* (2015)
Lebanon	1	1%	Boustani (2021)

(*continued*)

Table 2.
Country of analysis

Country	#	%	Exemplar studies
Saudi Arabia	1	1%	Aloud (2018)
Turkey	2	2%	Eren (2021), Tubadji *et al.* (2021)*
Country not reported	18	21%	Cavalcante *et al.* (2016), Huang and Philp (2020), Jakšič and Marinč (2019), Jung *et al.* (2018), Khandani *et al.* (2010), Konigstorfer and Thalmann (2020), Mhlanga (2020), Milana and Ashta (2021), Mogaji *et al.* (2020), Moscato *et al.* (2021), Mosteanu (2019), Payne *et al.* (2021a), Riikkinen *et al.* (2018), Truby (2020), Truby *et al.* (2020), Wall (2018), West and Bhattacharya (2016), Wexler and Oberlander (2021)

Table 2.

Note(s): * = Indicates multiple countries of analysis/data sources

Journal	#	ABDC ranking
Expert Systems with Applications	8	C
Strategic Change	6	C
Journal of Behavioral and Experimental Finance	5	A
International Journal of Bank Marketing	3	A
Journal of Research in Interactive Marketing	3	B
Australasian Marketing Journal	2	A
Computers And Security	2	A
Electronic Markets	2	A
European Business Organization Law Review	2	B
European Journal of Operational Research	2	A*
Journal of Business Research	2	A
Knowledge-Based Systems	2	A
Service Industries Journal	2	B

Table 3. Top 13 journals with most published articles

match the search string used by the researchers, supporting the choice of the search terms employed. Other frequently used keywords include *customer, learning, credit, machine, bank* and scoring*. While the keywords indicate a strong focus on information systems and computational technology (e.g. *algorithm, classification, ensemble and neural*), we also find many keywords that draw attention to customer behaviors (e.g. *decision, advice and satisfaction*) and the service context (e.g. *value, experience, quality and industry*).

4. General overview

The most important characteristics of systematic literature reviews include transparency, rigor and replicability (Snyder, 2019). However, authors can use different types of review structures, including framework-based (i.e. Paul and Benito, 2018), structured (i.e. Kahiya, 2018), bibliometric (i.e. Krishen *et al.*, 2021) or hybrid reviews (i.e. Vlačić *et al.*, 2021). For this study, we conducted a framework-based review, employing the *Method* TCCM framework, pioneered by Paul and Rosado-Serrano (2019). While relatively new, these authors' article is cited over 135 times, and numerous other studies use this framework (see Buitrago and Barbosa Camargo, 2021; Chen *et al.*, 2021; Lim *et al.*, 2021; Srivastava *et al.*, 2020).

4.1 Theory

Theoretical foundations and theory development are essential to academic research, as they foster avenues for further research and can contribute to the advancement of the discipline

Figure 3.
Keywords word cloud

(Hunt, 2018). A theory refers to a "systematically related set of statements, including some lawlike generalizations, that is empirically testable. The purpose of theory is to increase scientific understanding through a systematized structure capable of both explaining and predicting phenomena" (Hunt, 2010, p. 6). To better understand the underlying theoretical foundations of the reviewed papers, we have identified the theories applied or referred to and grouped them into related clusters: (1) economics and finance theories, (2) information systems theories, (3) organizational behavior theories, (4) psychological theories, (5) technology adoption theories, (6) value creation theories and (6) other theories. Prominent theories include the technology acceptance model (TAM) (Davis *et al.*, 1989), diffusion of innovation theory (Rogers, 1995) and modern portfolio theory (Markowitz, 1959). While 39% of studies use a single theory, 7% draw on multiple theories (e.g. Payne *et al.*, 2018; Xu *et al.*, 2020). Notably, most studies included in the review ($n = 58$) do not explicitly mention or apply a specific theory or theoretical framework (see Table 4).

The findings suggest a split between data-driven and theory-driven research. Theory-driven research in the traditional sense includes scientific inquiry, which begins with hypothesis development, data collection, data analysis and hypothesis testing. Researchers then draw theoretical conclusions from the results (Maass *et al.*, 2018). Data-driven research adopts an exploratory approach by applying analytical techniques and modes of reasoning to analyze data and obtain scientifically relevant insights (Maass *et al.*, 2018). While theory-driven research dominates the organization and social sciences, data-driven research is the primary research perspective in the natural and information systems sciences (Elragal and Klischewski, 2017).

Most articles employed theories categorized as either economics and finance ($n = 9$) or technology adoption ($n = 9$). In terms of technology adoption, most studies combined two or more theories, with some extending their frameworks with a third theory. In their application of the TAM combined with the unified theory of acceptance and use of technology (UTAUT),

Category	Key theory used	#	Exemplar studies
Agency	Contemporary financial intermediation theory	1	Jakšič and Marinč (2019)
	Agency theory	1	Bai (2021)
	General agency law	1	Lightbourne (2017)
Biology	Immune network theory	1	Lu *et al.* (2016)
Economics and Finance	Credit rationing theory	1	Mhlanga (2020)
	Economic theory	2	Boustani (2021), Tubadji *et al.*, 2021
	EMH theory (efficient market hypothesis)	1	Tokic (2018)
	Financial management theory*	1	Boustani (2021)
	Modern portfolio theory	3	Abdelazim and Wahba (2006), Chiu (2019), Shanmuganathan (2020)
	Rational choice theory	1	Bai (2021)
	Theory of financial innovation*	1	Boustani (2021)
	Contract theory	1	Mhlanga (2021)
	Adverse selection theory	1	Mhlanga (2021)
	Moral hazard theory	1	Mhlanga (2021)
Information Systems	Affordance-experimentation actualization theory*	1	Xu *et al.* (2020)
	Social response theory*	1	Adam *et al.* (2020)
	Transactive relationship theory*	1	Xu *et al.* (2020)
Organizational Behavior	Affective events theory	1	Henkel *et al.* (2020)
	Substitution and disruptive innovation theory	1	Rasiwala and Kohl (2021)
	Frugal theory of innovation	1	Abdulquadri *et al.* (2021)
	Theory of dynamic capabilities	1	Gallego-Gomez and De-Pablos-Heredero (2020)
Psychology	Attribution theory	1	Huang and Philp (2020)
	Commitment-consistency theory*	1	Adam *et al.* (2020)
	Expectation confirmation theory	1	Eren, 2021
	Theory of planned behavior	1	Atwal and Bryson (2021)
	Social representations theory (SRT)	1	Jang *et al.* (2021)
	Attitude–behavior model	1	Suhartanto *et al.* (2021)
Technology adoption	Diffusion of innovation theory*	3	Xu *et al.* (2020)
	Self-service technology adoption theory	1	Zhang *et al.* (2021a)
	Technology acceptance model*	6	Atwal and Bryson (2021), Belanche *et al.* (2019), Flavián *et al.* (2021), Payne *et al.* (2018), Seiler and Fanenbruck (2021), Xu *et al.* (2020)
	UTAUT*	2	Atwal and Bryson (2021), Mogaji *et al.* (2021)
Value creation	Value co-creation/co-destruction	3	Castillo *et al.* (2020), Payne *et al.* (2021a, b)
No guiding theory		58	Luo *et al.* (2019), Milana and Ashta (2021)

Note(s): * = The number of articles amounts to more than 90 as multiple articles draw on several theoretical perspectives

Table 4.
Key theories and theoretical frameworks

Atwal and Bryson (2021) seek to identify the determinants of consumer intentions to use robo-advisors. In a similar context, Zhang *et al.* (2021a) extend the self-service technology adoption theory. Meanwhile, Xu *et al.* (2020) draw on both the TAM and diffusion of innovation theory to investigate consumers' service preferences of AI vs humans, as well as the affordance–experimentation–actualization theory to demonstrate the numerous types of AI-enabled service encounters in a financial and banking context. With similar intent, Payne *et al.* (2018) also combine the TAM with the diffusion of innovation theory to identify explanatory factors influencing both consumers' attitudes and perceptions about AI-enabled mobile banking. While Flavián *et al.* (2021) do not explicitly employ the TAM, they include the key variables as control variables while studying the effect of technology readiness variables on the consumer's intentions to use robo-advisors. Other studies supplement agency theory with rational choice theory to examine the relationship between robo-advisory use and credit card debt (Bai, 2021) or adopt the attitude–behavior model lens to investigate AI-enabled mobile banking loyalty (Suhartanto *et al.*, 2021).

4.2 Context

Table 5 summarizes the contexts or types of customer-facing financial services investigated in the reviewed articles. The articles describe the investigated AI technology to varying degrees. While some discuss AI-enabled chatbots, robo-advisors or view AI in a general manner, others describe and apply technical terminology, including machine and deep learning algorithms (e.g. random forest, support vector machines and artificial neural networks). Identifying and explaining the different types of AI and ML methods is beyond the scope of this review and intended audience. Interested readers may consult Campesato (2020) and/or Sterne (2017).

4.2.1 Banking. Most studies (n = 27) focused on AI in the banking context. This is not surprising, given that banks represent the main financial service accessible to the wider population. Banks are increasingly relying on AI to improve the customer experience and expand their use of AI through conversational chatbots to assist customers with basic services or virtual assistants. Most banks consider AI technologies beneficial to the institution in various ways, including increasing revenues through improved customer service and reduced costs due to enhanced efficiencies, lower error rates and improved resource utilization (McKinsey and Company, 2020). Studies included in the review with a focus on banking included an investigation of the benefits and challenges of conversational software agents or chatbots (Adam *et al.*, 2020), whether chatbots can facilitate financial inclusion (Abdulquadri *et al.*, 2021), emerging market consumers' interaction and engagement with banking chatbots (Mogaji *et al.*, 2021) and how AI affects bank employees and customer behaviors when seeking out financial services (Boustani, 2021). Other studies use natural language processing to increase understanding of customer satisfaction (Piris and Gay, 2021), test AI's potential to reduce technical inefficiencies in commercial banks (Mor and Gupta, 2021), investigate consumer loyalty towards AI-enabled mobile banking (Suhartanto *et al.*, 2021) and study whether customers prefer AI or human online customer service applications (Xu *et al.*, 2020).

4.2.2 Financial advice and investment. One dominant area of AI research in financial services focuses on financial and investment advice using AI and robo-advisors. This was the second most dominant context in the reviewed articles (n = 24). Robo-advisors are used in the context of digital advisory services and rely on AI systems, which include automated platforms. Although robo-advisors provide numerous benefits, including service fee reductions and 24/7 consumer access, consumer adoption has been slow (Jung *et al.*, 2018). Bhatia *et al.* (2020) investigate whether and how robo-advisors could mitigate retail investors' behavioral biases. Brenner and Meyll (2020) find that robo-advice reduces the demand for human financial advice, especially for investors who fear investment fraud. Similarly, Atwal and Bryson (2021) explore private investors' robo-advisor adoption intentions, whereas

Article	General financial service 11% (n = 10)	Banking 30% (n = 27)	Financial advice and investment 27% (n = 24)	Credit scoring and risk assessment 24% (n = 22)	Regulation 11% (n = 10)	Fraud detection and prevention 1% (n = 1)
Abdelazim and Wahba (2006)			✓			
Abdulquadri *et al.* (2021)	✓					
Abellán and Castellano (2017)				✓		
Adam *et al.* (2020)		✓				
Aggarwal (2021)				✓		
Ala'raj and Abbod (2016)				✓		
Aloud (2018)			✓			
Ashta and Herrmann (2021)		✓	✓			
Atwal and Bryson (2021)			✓			
Baghdasaryan *et al.* (2021)				✓		
Bai (2021)			✓	✓		
Bejou *et al.* (1996)	✓					
Belanche *et al.* (2019)			✓			
Bhatia *et al.* (2020)			✓			
Borgogno and Colangelo (2019)					✓	
Boustani (2021)		✓				
Brenner and Meyll (2020)			✓			
Castillo *et al.* (2020)	✓					
Cavalcante *et al.* (2016)	✓					
Chiu (2019)					✓	
Correa Bahnsen *et al.* (2016)				✓		
Eren, 2021	✓					
Flavián *et al.* (2021)			✓			
Fulk *et al.* (2018)			✓			
Gallego-Gomez and De-Pablos-Heredero (2020)		✓				
Guo (2020)					✓	
Henkel *et al.* (2020)	✓					
Hildebrand and Bergner (2020)		✓				
Huang and Pan (2010)			✓			
Huang and Philp (2020)		✓				
Iiie *et al.* (2017)		✓				
Jakšič and Marinč (2019)	✓					
Jang *et al.* (2021)		✓				

Table 5.
Type of financial service

(*continued*)

Article	General financial service 11% (n = 10)	Banking 30% (n = 27)	Financial advice and investment 27% (n = 24)	Credit scoring and risk assessment 24% (n = 22)	Regulation 11% (n = 10)	Fraud detection and prevention 1% (n = 1)
Jung *et al.* (2018)			✓			
Kapsis (2020)					✓	
Kaur *et al.* (2020)	✓					
Khandani *et al.* (2010)				✓		
Khemakhem *et al.* (2018)				✓		
Konigstorfer and Thalmann (2020)		✓				
Koutanaei *et al.* (2015)				✓		
Kraus and Feuerriegel (2017)			✓			
Kruppa *et al.* (2013)				✓		
Kumar and Balaramachandran (2018)		✓				
Ładyżyński *et al.* (2019)		✓				
Lee (2020)					✓	
Lee and Shin (2020)		✓	✓			
Leung *et al.* (2009)			✓			
Lightbourne (2017)					✓	
Lu *et al.* (2016)		✓				
Lui and Lamb (2018)		✓				
Luo *et al.* (2019)	✓					
Mhlanga (2020)	✓					
Mhlanga (2021)			✓			
Milana and Ashta (2021)	✓					
Mogaji *et al.* (2020)	✓					
Mogaji *et al.* (2021)	✓					
Mor and Gupta (2021)		✓				
Moscato *et al.* (2021)				✓		
Mosteanu (2019)			✓			
Paleologo *et al.* (2010)				✓		
Payne *et al.* (2021a)						
Payne *et al.* (2018)		✓				
Payne *et al.* (2021b)	✓					
Philip *et al.* (2018)		✓				
Piris and Gay (2021)		✓				
Punniyamoorthy and Sridevi (2016)				✓		
Ramanathan and Wechsler (2013)	✓					
Rasiwala and Kohl (2021)			✓			
Riikkinen *et al.* (2018)		✓				
Seiler and Fanenbruck (2021)			✓			

(continued)

Table 5.

Article	General financial service 11% (n = 10)	Banking 30% (n = 27)	Financial advice and investment 27% (n = 24)	Credit scoring and risk assessment 24% (n = 22)	Regulation 11% (n = 10)	Fraud detection and prevention 1% (n = 1)
Shanmuganathan (2020)			✓			
Singh *et al.* (2021a)				✓		
Suhartanto *et al.* (2021)		✓				
Sun and Vasarhelyi (2018)				✓		
Tokic (2018)			✓			
Trivedi (2019)				✓		
Truby (2020)					✓	
Truby *et al.* (2020)					✓	
Tubadji *et al.* (2021)	✓					
van Thiel and van Raaij (2019)				✓		
Wall (2018)					✓	
West and Bhattacharya (2016)						✓
Wexler and Oberlander (2021)		✓	✓			
Xu *et al.* (2020)		✓				
Yu *et al.* (2009)				✓		
Zeinalizadeh *et al.* (2015)		✓				
Zhang *et al.* (2019)				✓		
Zhang *et al.* (2021a)			✓			
Zhang *et al.* (2021b)				✓		
Zhu *et al.* (2013)				✓		

Table 5.

Note(s): The number of articles amounts to more than 90 as select articles fall within two groups

Flavián *et al.* (2021) investigate the effect of customers' service awareness and technology readiness on their intention to use robo-advisors. However, not all articles focused on financial advice and investment management were concerned with robo-advisors, with some investigating AI applications in trading systems and forecasting financial markets (Aloud, 2018) or portfolio selection and management (Abdelazim and Wahba, 2006) instead.

4.2.3 Credit scoring and risk assessment. Another dominant research context (n = 22) included studies investigating AI and ML techniques to assist financial institutions in identifying credit risks and providing overall customer credit scores. In this context, AI methods are implemented to assess the probability of customers failing to repay a loan or debt, which would result in losses for the financial institution. All the reviewed studies focusing on credit scoring and risk assessment involved technical analysis of the effectiveness and accuracy of different AI and ML algorithms (Ala'raj and Abbod, 2016; Correa Bahnsen *et al.*, 2016; Singh *et al.*, 2021a; Trivedi, 2019; Zhu *et al.*, 2013), except for Aggarwal (2021), who discusses algorithmic credit scoring from a regulatory perspective instead and Mhlanga (2021), who reviews the literature on credit risk assessment in the context of financial inclusion and emerging economies.

4.2.4 General financial services. Select articles (n = 10) refer to AI in the general context of financial services. For example, Ashta and Herrmann (2021) investigated the role of AI in creating various opportunities for financial organizations while also highlighting the inherent risks associated with this new technology. Henkel *et al.* (2020) examine whether AI-based emotion recognition software can support service employees in customer emotion management. Taking a value creation perspective, Castillo *et al.* (2020) considered the consequences of AI-powered chatbot service failures, including financial technology support, investment and banking support.

4.2.5 Regulation. The fifth and final context we identified focuses on regulation. Although AI brings many benefits, increasingly sophisticated technologies also increase the potential for abuse. Financial institutions are concerned with data ownership, consumer privacy and cybersecurity (Truby *et al.*, 2020). Regulation is needed to address these concerns, as uncontrolled innovation can have devastating consequences (Accenture, 2019). Although an increasingly important research area, only $n = 10$ articles included in the review adopted a regulatory focus. Regulation affects all areas of financial services, including banking, investment, credit scoring and financial advice. For example, Chiu (2019) discusses different regulatory frameworks to improve trust and credibility perceptions in the financial advice industry, including robo-advisors' implications and current limitations (Lightbourne, 2017). Guo (2020) highlights legitimacy issues concerning robo-advisors, which they in part attribute to a lack of investor protection and information asymmetry. Select studies investigate the role of AI in increasing financial inclusion, with some focusing on the regulatory environment. For example, both Lee (2020) and Truby (2020) discuss the design of regulatory and legal frameworks focusing on the use of AI, stressing that clear policies are needed to ensure fair and equitable access to finance.

4.3 Characteristics

For this review, we have separately reviewed the characteristics (variables) tested in the quantitative studies ($n = 51$) and themes identified in the qualitative studies ($n = 39$), including conceptual and mixed method studies. We commence with a discussion of the quantitative article variables, followed by a review of qualitative themes.

Researchers have conducted quantitative research to investigate several variables relating to consumers, service firms and technology (see Figure 4). We categorize these according to their role, distinguishing between independent, mediating, moderating and dependent variables. Within each group, we further classify variables into separate groups based on the entities they primarily relate to (e.g. consumer-related variables, firm-related variables and technology-related variables).

4.3.1 Independent variables. Figure 4 shows the different subgroups of typically investigated independent variables. Consumer-related variables are grouped into five sub-groups, including technology perceptions ($n = 6$; 12%), consumer beliefs ($n = 7$; 14%), service experience ($n = 10$; 20%), financial behavior ($n = 3$; 6%) and sociodemographic variables ($n = 2$; 4%). Several studies test independent variables belonging to separate groups. For example, Payne *et al.* (2018) test both subjective norms as a consumer belief variable and quality of service as a service experience variable. Studies focusing on consumer-related variables show that consumer attitudes, interpersonal subjective norms/social influences, perceived ease of use and usefulness are key determinants of robo-advisor adoption (Belanche *et al.*, 2019). Fulk *et al.* (2018) demonstrate that robo-advisory users differ in income, net worth, being an inheritance recipient or not, and financial impulsivity, while Zhang *et al.* (2021a) find that consumers continue to prefer expert human financial advisors as opposed to robo-advisors, while they find no significant differences between robo-advisors and novice human advisors in terms of performance expectancy and hiring intentions. Additionally, select studies find that once AI is introduced to a digital self-service channel, such as mobile banking, both service delivery and the customer's value co-creation role change (Payne *et al.*, 2021b), while others find that consumers perceive AI's problem-solving abilities with less

Independent Variables/ Antecedents

Consumer-related (34%; 17 articles)*

- *Technology perceptions (12%; 6 articles)*
  - Perceived usefulness
  - Perceived ease of use
  - Performance expectancy
  - Use of AI as a financial innovation
  - Technology readiness (optimism, innovativeness, discomfort, insecurity)
- *Consumer beliefs (14%; 7 articles)*
  - Subjective norms
  - Perceived trust
  - Attitudes
  - Fear of investment fraud
  - Religiosity
- *Service experience (20%; 10 articles)*
  - Customer expectations
  - Perceived performance
  - Confirmation of customer expectations
  - Service outcome
  - Convenience, equipment, cleanness, appearance & atmosphere of the bank
  - Quality & Tariffs
  - Availability & performance of e-banking
  - Enhanced (online) customer experience
  - Need for service
  - Relative advantage
  - Baseline perception of service delivery
  - Service awarenes
- *Financial behavior (6%; 3 articles)*
  - Perceived ability as investor
  - Feelings of earning enough money
  - Financial & investment acumen
  - Saving behavior
  - Impulsivity
  - Financial satisfaction
  - Number of credit cards
  - Online loan inquiries
  - Loan amount
  - Credit card spending
  - Online spending
  - Customer voice pitch
  - Robo-user
- *Sociodemographic (4%; 2 articles)*
  - Age, gender, education, household income, net worth, inheritance, marital status

Firm-related (6%; 3 articles)

- *Firm characteristics (4%; 2 articles)*
  - Seller's ethical orientation
  - Seller's expertise
  - Relationship duration
  - Customer & selling orientation
  - Corporate reputation
- *Employee/ Job characteristics (2%; 1 article)*
  - AI augmentations vs. control

Technology-related (13%; 6 articles)

- *Interface specifications (9%; 4 articles)*
  - Interface conditions: Conversational vs. Non-Conversational Robo Advisor
  - Anthropomorphic design cues (Identity, Empathy & Smalltalk)
  - Quantity of online devices(other than AI) that the consumer uses
- *Technology characteristics (8%; 4 articles)*
  - Security, privacy and risk
  - Reliability
  - Human-like interaction

Moderating variables

- *Social factors (4%; 2 articles)*
  - Social presence
- *Sociodemographic factors (2%; 1 article)*
  - Age, gender, country
- *Technology-related factors (12%; 6 articles)*
  - Perceived performance
  - Perceived trust
  - Interpersonal emotion regulation (IER) activity
  - AI system personalization (Yes vs No)
  - Task complexity
  - Familiarity with robots
- *Firm-related factors (2%; 1 article)*
  - Corporate reputation
- *No moderator (21%; 10 articles)*

Mediating variables

- *Social factors (2%; 1 article)*
  - Social presence
- *Psychological factors (9%; 4 articles)*
  - Attitude
  - IER goal attainment,
  - Perceived stress related to AI exposure
  - Affective trust towards robo-advisor
  - Self-AI connection
- *Service perceptions (4%; 2 articles)*
  - Confirmation of Customer Expectations
  - Perceptions of AI Service Delivery
- *Technology-related factors (4%; 2 articles)*
  - Service delivery configuration benefits
  - General data security
  - Perceived problem-solving ability of AI
- *No mediator (17%; 8 articles)*

Dependent Variables/ Outcome

Consumer-related (34%; 16 articles)

- *Adoption intention & usage (20%; 10 articles)*
  - User compliance
  - Intention to adopt/ use/ hire AI
  - MB usage & comfort using AI mobile banking services
  - Value-in-use perceptions
  - Bank client's acceptance
  - Appeal that AI technology has for the consumer
  - Human financial advice
- *Satisfaction (9%; 4 articles)*
  - Customer satisfaction
  - Negative word of mouth
  - Time efficiency on clients
- *Financial behaviour (6%; 3 articles)*
  - Help seeking behaviour
  - Purchase (loan renewal)
  - Banking loyalty
- *Value creation/ destruction (2%; 1 article)*
  - Customer resource loses (role clarity, emotional, relational, temporal & informational)
- *Well-being (2%; 1 article)*
  - Affective well-being

Firm-related (6%; 3 articles)

- *Firm characteristics (2%; 1 article)*
  - Transformation of the banking profession
  - Fluctuations in banking jobs removal & creation
  - Soft competence jobs requirements
- *Firm perception (2%; 1 article)*
  - Benevolence attribution toward financial services firm
  - Recommendation acceptance
  - Portfolio allocation
- *Firm-consumer relationship(2%; 1 article)*
  - Relationship quality

Note(s): * = percentage scores are based on 51 quantitative studies

Figure 4.
Summary of quantitative variables

complex tasks to be greater than that of humans; however, human customer service is viewed as superior for more complex problems. Apart from service quality, technology attitudes and perceived trust, Suhartanto *et al.* (2021) also reveal religiosity as an important driver of Indonesian Millennials' loyalty regarding AI-enabled mobile banking. Lastly, Huang and Philp (2020) show that consumers are less likely to share negative word of mouth after AI-caused service failure compared to human-caused service failure.

In total, 34% of independent variables were consumer-related, whereas only 6% were firm-related, including firm characteristics (n = 2; 4%) and employee/job-related variables (n = 1; 2%). Study results suggest that customer satisfaction depends on the experience and ethics of the salesperson as well as the degree of customer orientation (Bejou *et al.*, 1996) and corporate reputation (Eren, 2021). Henkel *et al.* (2020) find that service employees' interpersonal emotion regulation skills are significantly enhanced in their effectiveness after being augmented by AI.

Lastly, select studies included in the third group consisting of technology-related variables examined variables concerning interface specifications (n = 4; 8%) and technology characteristics (n = 4; 8%), resulting in an overall relative frequency of 14% of technology-related variables. Hildebrand and Bergner (2020) find that conversational robo-advisors, as opposed to nonconversational/static ones, increase consumers' trust and affirm their positive evaluations of the firm. Additionally, anthropomorphic design cues including identity, empathy and small talk increase the likelihood of users' compliance with chatbot service requests (Adam *et al.*, 2020).

4.3.2 Mediating variables. We found that 9 out of 50 articles (18%) include mediating variables. While researchers have long recognized the importance of mediating variables to explain the underlying mechanism of findings (Baron and Kenny, 1986), several studies did not include any mediators (Bejou *et al.*, 1996; Eren, 2021; Payne *et al.*, 2018). Mediation is concerned with the intervening effect of a third variable on the main effect between independent and dependent variables. Most included mediators concern (1) psychological factors, followed by (2) service perception variables, and (3) technology-related factors. Psychological factors include attitude (Belanche *et al.*, 2019), interpersonal emotion regulation goal attainment and stress (Henkel *et al.*, 2020), affective trust towards robo-advisors (Hildebrand and Bergner, 2020) as well as self-AI connection (Huang and Philp, 2020). Service perception mediators include confirmation of customer expectations (Eren, 2021) and perceptions of AI service delivery (Payne *et al.*, 2021a). Technology-related factors include service delivery configuration benefits and general data security (Payne *et al.*, 2021b), as well as AI's perceived problem-solving ability (Xu *et al.*, 2020). Adam *et al.* (2020) find that social presence mediates the relationship between anthropomorphic design cues and user compliance with chatbot requests.

4.3.3 Moderating variables. Our review indicates that 7 out of 50 (14%) studies consider moderating variables, which can affect the strength or direction of the relationship between an independent and dependent variable (Baron and Kenny, 1986). Most included moderating variables fall within the technology category, such as perceived performance and trust (Eren, 2021), interpersonal emotion regulation activity (Henkel *et al.*, 2020), task complexity (Xu *et al.*, 2020) and previous experience (Flavián *et al.*, 2021) or familiarity with robots (Belanche *et al.*, 2019). Through a moderated mediation analysis, Huang and Philp (2020) find that AI system personalization moderates the service outcome (independent) and self-AI connection (mediator) effect. This suggests that due to the personalized nature of AI, consumers have a closer connection with it and are less likely to share negative word of mouth in response to AI-caused service failure. Adam *et al.* (2020) find that social presence mediates the effects of anthropomorphic design cues on user compliance but did not find a moderating effect of social presence on the same relationship.

4.3.4 Dependent variables. Our review of dependent variables shows that most studies focus on consumer-related outcomes (n = 18; 36%), while only few (n = 3; 6%) focus on firm-related outcomes. Consumer-related outcomes include (1) adoption intention and usage, (2) satisfaction, (3) financial behavior, (4) value creation/destruction and (5) well-being groups. We group firm-related outcomes into (1) firm characteristics, (2) firm perception and (3) the firm–consumer relationship.

Referring to consumer-related outcomes, prior studies primarily focused on adoption intention and usage (n = 10; 20%), considering dependent variables, such as user compliance (Adam *et al.*, 2020), intention to use (Belanche *et al.*, 2019; Flavián *et al.*, 2021; Seiler and Fanenbruck, 2021; Xu *et al.*, 2020), mobile banking usage and comfort using AI-mobile banking services (Payne *et al.*, 2018), intention to hire (Zhang *et al.*, 2021a), bank clients' acceptance (Boustani, 2021) and the appeal AI has for consumers (Tubadji *et al.*, 2021). Dependent variables in the satisfaction group (n = 4; 8%) included customer satisfaction (Eren, 2021), negative word of mouth (Huang and Philp, 2020) and bank clients' satisfaction and time efficiency effects on clients (Boustani, 2021). Few studies considered consumer financial behaviors as outcome variables. Only three financial behaviors were investigated, namely help-seeking behavior (Fulk *et al.*, 2018), purchase (customers' loan renewal) (Luo *et al.*, 2019) and banking loyalty (Suhartanto *et al.*, 2021). Both Castillo *et al.* (2020) and Payne *et al.* (2021b) focus on value creation/destruction outcomes by investigating antecedents of customer resource losses and value-in-use perceptions of AI-based mobile banking applications.

While the majority of studies investigated consumer-related dependent variables, three studied firm-related outcomes, including the transformation of the banking profession, fluctuations in banking jobs removal/creation and soft competence job requirements (Boustani, 2021), firm perception (benevolence attribution toward financial services firm, recommendation acceptance and portfolio allocation) (Hildebrand and Bergner, 2020) and relationship quality (Bejou *et al.*, 1996).

As we did not limit our data collection to quantitative articles, our review also includes numerous qualitative and conceptual studies (n = 40), which are not concerned with empirically testing hypothesized relationships. Instead, qualitative studies seek to develop themes to gain new insights into a research domain, while conceptual articles aim to advance theoretical considerations (Fossey *et al.*, 2002). Table 6 provides an overview of identified themes, including (1) perceptions on innovation/digital disruption (Rasiwala and Kohl, 2021), (2) customer satisfaction (Piris and Gay, 2021), (3) service failure (Castillo *et al.*, 2020), (4) robo-advisor (Bhatia *et al.*, 2020; Wexler and Oberlander, 2021), (5) regulation (Aggarwal, 2021), (6) AI implications for digital marketing (Mogaji *et al.*, 2020) and (7) value creation (Payne *et al.*, 2021a; Riikkinen *et al.*, 2018).

While we considered all 51 quantitative studies, including survey-based and experimental studies, articles investigating and contrasting the specific applicability and functionalities of AI and ML algorithms did not provide identifiable independent or dependent variables (n = 26). Given that a discussion regarding the details on the types of algorithms investigated is beyond the scope of the present review, we provide a list of these articles for interested readers in Appendix 2.

4.4 Methods

Table 7 summarizes the research design characteristics of the reviewed studies, including the adopted empirical approach, target sample and sample size. Among the 90 studies, 57% conducted quantitative research, 29% were qualitative, 7% were conceptual and 8% employed mixed methods. The use of experimental and survey data is unequally distributed, with 32 articles (38%) employing an experimental and 17 (20%) employing a survey research approach. Experimental studies are further divided into data-driven and theory-driven research. That is, 22 experimental studies employed algorithms and information systems (IS) software for data collection and/or data analysis (e.g. Correa Bahnsen *et al.*, 2016; Huang and Pan, 2010; Kraus and Feuerriegel, 2017), whereas the remaining ten used either 2 × 2

Category	#	% *	List of themes
Perceptions on innovation/ digital disruption	4	10	1. Disruptors in the financial sector and their business models; 2. Level of competition, threat of substitution; 3. Technological capabilities and omni-channel strategies for consumers; 4. Support provided by regulators and government; 5. Entrepreneurship and innovation; 6. The future of the two sectors (finance and technology) (Rasiwala and Kohl, 2021) 1. Technology innovation; 2. Social innovation; 3. Institutional innovation - > banks, chatbot, customers - > financial services provision and financial inclusion (Abdulquadri *et al.*, 2021) 1. Technological immatureness; 2. Improving customer experience; 3. Supportive role; 4. Lack of organizational capability; 5. Organizational resistance; 6. Improving operational efficiency; 7. Experiment; 8. Collaboration with tech firm; 9. Extensive investment; 10. Substitute role; 11. Artificial intelligence (AI); 12. Developing new service model; 13. Strict government regulation; 14. Responding to customers who prefer nonfacing channels; 15. Facilitating digital transformation (Jang *et al.*, 2021) 1. Performance expectancy (sense of accomplishment and enhanced engagement); 2. Effort expectancy (task accomplishment, perceived ease and access); 3. Social influence (user interface, no public display and bank's influence); 4. Facilitating conditions (Chatbot's features, bank's features and country features); 5. Moderating factors with chatbots (age, experience and voluntariness) (Mogaji *et al.*, 2021)
Customer satisfaction	1	3	1. Internet site and mobile applications; 2. Day-to-day operations of the accounts and contracts; 3. The relational and human dimension; 4. Means of communication; 5. Attitude towards the institution; 6. The brick-and-mortar branch; 7. Mortgages; 8. Pricing policy (Piris and Gay, 2021)
Service failure	1	3	5 antecedents of failed interactions between customers and chatbots: 1. authenticity issues; 2. cognition challenges; 3. affective issues; 4. functionality issues; and 5. integration conflicts (Castillo *et al.*, 2020)
Robo-advisor	5	13	(1) Present state of robo-advisory: 1. Usage of robo-advisory; 2. Educating investors on robo-advisory services; 3. Trust and branding: Essential for acceptance of robo-advisors; 4. A consortium of banks for untapped segments (2) Risk profiling: 1. Framework for risk profiling; 2. Risk profiling through a psychological perspective; 3. Risk Appetite should be linked to investment goals; 4. Different models of risk profilers; 5. Measuring investor's risk appetite; 6. Difficult to track financial goals of investors (3) Mitigation of behavioral biases: 1. Less biased Robo advisors mitigates more behavioral biases, 2. A hybrid model for non tech savvy and financially illiterate investors, 3. Biases in questionnaire 4. Biases in Architecture (Bhatia *et al.*, 2020)) 1. Characteristics of RAs: Disembodied, programmed, calculation rationality, client-controlled, current, trustworthy, big data, AI; 2. RA introductions: Experiment, voluntary, auxiliary, knowledge worker friendly, client friendly, investor friendly, centrality of industry, on trend; 3. Knowledge features: Technological augmentation, coded programs, digitalization, trending, do-it yourself, active learning, customizable, credentialled (Wexler and Oberlander, 2021) 1. Platform; 2. Ease of navigation; 3. Controllability; 4. Structural consistency; 5. Error tolerance; 6. Effectiveness; 7. Efficiency; 8. Expectation conformity; 9. Understanding; 10. Social presence; 11. Cost; 12. Infrastructure; 13. Process (Jung *et al.*, 2018) 1. Quantitative inputs (financial statement and other relevant data); 2. Subjective inputs (corporate governance and knowledge-base); 3. Algorithms-based learning model; 4. Robo-advisors; 5. Feedback; 6. Clients investment decision (Shanmuganathan, 2020) 1. Perceived risk; 2. Perceived usefulness; 3. Perceived ease of use; 4. Social influences; 5. Intention to use (Robo-advisors) (Atwal and Bryson, 2021)

(*continued*)

Table 6. Qualitative research themes and conceptualizations

Category	#	% *	List of themes
Regulation	2	5	Allocative efficiency, distributional fairness, privacy (autonomy) (Aggarwal, 2021)** 1. Regulation of algorithms of robo-advisors; 2. Improvement of information disclosure requirements; 3. Refinement of fiduciary duties of robo-advisors (Guo, 2020)
AI implications on digital marketing	1	3	Four processes: 1. AI (data extraction, processing and learning); 2. AI integration with digital marketing (algorithmic content creation and delivery, customer identification, personalized messaging); 3. AI integration with digital financial services marketing; 4. Financial services use of AI to serve vulnerable customers (positive and negative) (Mogaji *et al.*, 2020)
Value creation	2	5	AI-service exchange antecedents: consumer characteristics (utilitarian and hedonic value), financial industry characteristics, FinTechs supporting institutional actor characteristics; context of AI usage: Lower and higher value-in-use AI contexts; digital servitization consequences: consumer outcomes and firm performance outcomes (Payne *et al.*, 2021a) Using AI and chatbots to create value: Technological perspective (AI and leveraging customer data), theoretical perspectives (service logic and customer data as a resource), industry phenomenon (transfer of resources and processes/digitalization) (Riikkinen *et al.*, 2018)
No clear themes/categories identified	24	61	Ashta and Herrmann (2021), Borgogno and Colangelo (2019), Cavalcante *et al.* (2016), Chiu (2019), Gallego-Gomez and De-Pablos-Heredero (2020), Jakšič and Marinč (2019), Kapsis (2020), Kaur *et al.* (2020), Khemakhem *et al.* (2018), Konigstorfer and Thalmann (2020), Lee and Shin (2020), Lee (2020), Lightbourne (2017), Lui and Lamb (2018), Mhlanga (2020), Mhlanga (2021), Milana and Ashta (2021), Mosteanu (2019), Paleologo *et al.* (2010), Philip *et al.* (2018), Tokic (2018), Truby (2020), Truby *et al.* (2020), Wall (2018), West and Bhattacharya (2016)

Note(s): * = Relative frequencies based on 39 qualitative articles (including interviews, conceptual, case study, review and mixed methods), ** = normative contests on regulation

Table 6.

experimental designs (Adam *et al.*, 2020) or randomized controlled trial field experiments (Luo *et al.*, 2019; Xu *et al.*, 2020). Lastly, Abdulquadri *et al.* (2021) employ the Search-Access-Test (S-A-T) model, a novel research methodology combining user experience design and netnography.

Most studies include secondary data from publicly available datasets. Due to this, sample sizes for certain studies exceeded 1,000 observations. For example, Correa Bahnsen *et al.* (2016) conducted experiments using a dataset of 236,735 credit/debit card transactions obtained from a large European card processing company, whereas Philip *et al.* (2018) used a sample of 100,000 loan accounts, consisting of monthly loan repayment data. Interestingly, several studies appear to have utilized similar datasets to test their AI technique (e.g. Abellán and Castellano, 2017; Ala'raj and Abbod, 2016; Zhang *et al.*, 2019, 2021b). These articles focused on testing the applicability of different AI techniques on credit scoring using datasets obtained from the University of California at Irvine (UCI) Machine Learning Repository at the University of California (Asuncion and Newman, 2007).

5. Directions for future research

Our systematic literature review yields a broader understanding of various theoretical aspects and different applications of AI in the financial services industry (van Esch *et al.*, 2020). While the present literature offers different perspectives on the applicability and usefulness of AI, we posit that the field offers many unexplored yet fruitful areas for further research. We suggest that researchers use the proposed research topics and questions as guides to develop and empirically

Design element	#	%
Empirical approach		
Quantitative		
Survey	17	20
Experiment	32	38
Field study	1	1
S-A-T (novel methodology)	1	1
Qualitative		
Case study	4	5
Interviews	6	7
Review	7	8
Regulatory review	6	7
Opinion paper	1	1
Document analysis	1	1
Exploratory research	1	1
Conceptual	6	7
Mixed methods	7	8
Type of sample		
Customers/Investors	24	28
Managers/Experts/Employees	6	7
Companies	6	7
Datasets	22	26
Other	11	13
Not specified	19	22
Sample size		
1–100	22	26
101–500	15	18
501–1,000	8	9
1,000+	25	29
Not specified	20	24

Table 7. Research design characteristics

test propositions and hypotheses, while others may wish to consider theory development. In line with previous reviews (Chen *et al.*, 2021; Mandler *et al.*, 2021; Paul *et al.*, 2017), we organize our recommendations as per the structure of the preceding analysis along the TCCM framework. We thus divide the future research agenda into four segments: (1) new theoretical perspectives (*theory),* (2) new research settings (*context),* (3) new constructs and relationships (*characteristics)* and (4) new data and methods (*methodology).* Table 8 provides an overview of suggested research directions for each area, along with examples of potential research questions.

5.1 New theoretical perspectives

Most studies included in the review (64%) adopt a data-driven approach and lack a strong theoretical foundation, providing researchers with ample future research opportunities. We suggest several theories and conceptual lenses for future investigations, including theories from marketing communication, organizational behavior, decision-making and services marketing (van Esch and Stewart Black, 2021). Advances in big data and computational processing allow social sciences research to combine theory- and data-driven research, increasing its validity and reliability (Maass *et al.*, 2018). The following section summarizes each proposed theory and its applicability to the research domain under investigation.

5.1.1 Resource integration and service ecosystem lens (S-D logic). Given the service-focused nature of the research domain, select studies have adopted a service-dominant logic lens to investigate value co-creation processes in banking (Payne *et al.*, 2021a) and insurance

Potential research topics and guiding questions	
New theoretical foundations (theory)	
Resource integration and service ecosystem lens (S-D logic)	How can AI be used to facilitate information creation, dissemination and sharing amongst ecosystem actors? What constitutes AI-enabled financial service encounters? How does the coordination of engagement between different actors in the context of financial services take place? Ecosystem integration: What are the challenges of integrating AI into existing systems and processes of financial institutions?
Customer-dominant logic (CDL) and value-in-use	How is value-in-use expressed in the context of AI adoption in financial services? How and when can AI-augmented financial service value-in-use be measured? What role does marketing play in enhancing consumer acceptance of AI in financial service provision? How does AI affect the value co-creation process (will control shift to the consumer)?
Actor–network theory and activity theory	What role should financial services managers/marketers take in designing AI-based services? How does artificial intelligence drive the digital transformation of the financial services industry? What impact does AI have on all aspects of the activity system, including the subject, object, or community? How can activity theory and ANT be applied to study the role of AI in developing new activity system networks?
Grounded theory	What constitutes algorithmic culture and what are the implications for financial institutions? Adopting a holistic approach, how should do we describe AI/robo-advisor capabilities in a financial service context? What constitutes AI-supplemented financial advice and how does AI-augmented customer service differ conceptually from human-provided customer experience?
New research settings (context)	
Insurance	How can artificial intelligence and augment or replace current insurance claim systems and processes? What is the impact of data and open-source protocols on AI implementation in an insurance context? To what extent does AI influence insurance ecosystem creation or extension?
Financial well-being and behavior	How can AI reduce financial vulnerability? To what extent can AI mitigate the emotional distress experienced by consumers? How can AI assist consumers in the management of a crisis? How can artificial intelligence be employed to improve an individual's financial capability and overall financial well-being? How can AI empower consumers with disabilities/vulnerable people? How can AI be used to increase pension member engagement through customer journey mapping or personalization efforts? To what extent do consumer (financial) literacy and information asymmetry affect their anticipated adoption of AI-augmented services such as robo-advisors or chatbots?

(*continued*)

Table 8.
Future research agenda

Potential research topics and guiding questions	
Pensions	How can AI be used to increase pension member engagement through customer journey mapping or personalization efforts? How willing are consumers in accepting AI application of pension investment selection? How does AI perform in comparison to traditional investment managers/funds? To what extent can AI be employed as a tool to monitor fund and investment performance?
Digital economy	To what extent does AI facilitate the growth of financial services in the context of the digital economy In what ways does AI shape financial service ecosystems and the digital economy, and what are the consequences for financial institutions and consumers? How can AI be applied to align and integrate cross-country financial data? To what extent can AI ensure transparency and equity between merging and developed economies?
Ethics, legal and policy	What constitutes ethical and socially responsible AI provision (firm) or adoption (consumer)? How can AI be used to enhance personalization efforts in financial service? What type of data is required and can be acquired? To what extent are consumers willing to share additional information in exchange for increased personalization? What regulation is required to address the potential risks posed by third-party vendor management? The privacy-security gap: How can AI be utilized to monitor and detect financial crime/fraud while not infringing consumer privacy? What role do individuals/employees/managers/developers play in ethical considerations of AI?
New research constructs and relationships (characteristics)	
Customer engagement	What role do interactivity and personalization play in stimulating customer engagement with AI? How can financial services firms use AI to optimize the customer experience in an omnichannel environment? How can AI-generated real-time insights of transactional service interactions be used to increase customer engagement?
Financial knowledge and behavior	What role do information asymmetry, literacy and self-directedness have on AI-enhanced financial decision-making? What effects do self-efficacy and perceived financial security have on AI-augmented service experiences? Does AI-augmented service uptake depend on the different types of financial decisions (routine vs consequential)? What role does AI play in improving financial risk tolerance and savings goal clarity; conscientiousness and proactivity; emotional stability, financial anxiety, and money management stress? What role do behavioral biases, herding behavior, bounded rationality and people's emotions play in AI acceptance? Will individuals with low literacy make worse or better financial decisions if assisted by AI?

(*continued*)

Table 8.

Potential research topics and guiding questions	
Technology acceptance	How can integrated marketing communication be used to increase the consumer's acceptance of AI in financial services? How does AI affect the (digital) information flow, and what roles do consumer information avoidance and information-seeking behaviors play?
New data and methods (methodology)	
Bias testing	Future quantitative research studies should analyze and account for various biases to ensure increased validity of research findings Apply post-hoc, procedural and statistical remedies to detect and remedy common method variance (CMV)
Alternative methods (netnography)	Utilizing netnography and text mining techniques, future research can measure the consumer's AI-related attitudes and sentiments
Longitudinal data	Future research may collect longitudinal data to test if the consumer's AI-augmented financial services experience changes over time and how? How long does it take for artificial intelligence to ensure financial inclusion? To what extent can artificial intelligence assist in ensuring long-term financial well-being?
Meta-analysis	Call for an updated meta-analysis on the efficacy of AI in investment banking Additional topics for meta-analysis include trust in or acceptance of robo-advisors or meta-analysis on AI adoption in a banking context, either taking a consumer or an organizational point of view

Table 8.

(Riikkinen *et al.*, 2018). However, these studies are limited, in part due to their conceptual nature as empirical examinations are required to further and support a theoretical concept (Larivière *et al.*, 2017). Vargo and Lusch (2017) recommend future research to subject SD logic-generated theory to increasing empirical scrutiny. While some studies in the review have commenced empirically testing value co-creation through the lens of SD logic and ecosystem perspective (Castillo *et al.*, 2020; Payne *et al.*, 2021b), many research avenues remain open. Future research may wish to investigate service innovation focusing on resource integration, resource liquefaction, density creation or actor networks (Lusch and Nambisan, 2015). Additionally, technology acts as an enabler of relationships and connections amongst various actors within an ecosystem (Larivière *et al.*, 2017). However, the impact of AI on creating or destroying these connections remains unexplored to date.

5.1.2 Customer-dominant logic (CDL) and value-in-use. Heinonen *et al.* (2010) posit that the SD logic (Vargo and Lusch, 2004) continues to apply a production- and interaction-focused lens to service, thus viewing service co-creation primarily from the service provider's perspective. According to Vargo and Lusch (2008, p. 213), value is "always uniquely and phenomenologically determined by the beneficiary." As the objective of service provision, in part, is to increase value for the consumer, we suggest future marketing and service research to adopt a customer-dominant logic (CDL) lens. CDL recognizes marketing to be foundational for business instead of a mere functional unit within an organization (Heinonen and Strandvik, 2015). Much is yet to be understood about this perspective, but research using CDL in the context of AI in financial services is largely missing, which provides researchers with numerous opportunities for future research. For example, future researchers may wish to explore the concepts of co-creation, by focusing on consumer involvement and control or customer experience (van Esch and Cui, 2021) and value-in-use, with the latter focusing on visibility and consumer competence (Heinonen *et al.*, 2010; Sandstrom *et al.*, 2008).

5.1.3 Actor–network theory and activity theory. While some researchers may want to adopt an SD logic or CD logic lens to examine AI in financial services, others may turn to actor networks. While studying the impact of technology on actor networks and ecosystems is not a new area of research, ongoing technological developments continue to demand research attention. For example, actor–network theory (ANT) seeks to explain sociotechnological development and change, with its main tenets including actors and networks, where actors can be both human and nonhuman (Baiocchi *et al.*, 2013). According to Latour (1987), ANT combines elements of science and technology, allowing researchers to unpack and investigate basic components, including networks, actors, environments, policies and processes. AI poses an interesting viewpoint, as it is considered a nonhuman actor, but with human capabilities. Using the ANT, future research may analyze the constructed network of financial service actors and explore how well AI fits the role of an actor therein or examine the process of translation in the context of AI-augmented financial services.

Activity theory (AT) is another sociotechnical theory, which focuses on interpreting human consciousness as a result of an individual's everyday interactions and practical activity (Nehemia-Maletzky *et al.*, 2018). It suggests that human–computer interactions are driven by social motives and recognizes the increasingly digitalized nature of human activity (Karanasios *et al.*, 2021). AI increases the complexity of human–machine conglomerations in many organizational contexts, including financial services. As such, it requires researchers to investigate the increasingly complex forms of agency and different types of collaboration and inter-connecting activity systems (Balyone, 2019). Future research could study the role of AT in addressing practical and theoretical challenges and opportunities resulting from the increased application of AI in financial services.

5.1.4 Grounded theory. Due to the innovative nature of AI and the utilitarian attributes of financial services, we propose researchers adopt a grounded theory approach (Gioia *et al.*, 2013). To date, marketing scholars employ and extend existing theories, borrowing from related disciplines, such as psychology and economics. However, theory development is critical to the advancement of marketing as a research domain (MacInnis, 2011), and grounded theory researchers could explore how AI can improve consumer decision-making and financial well-being.

5.2 New research settings

Concerning the investigated contexts, our review identified banking and credit scoring/risk assessment to be well-represented. However, studies exploring other contexts remain scarce. While some reviewed studies started to investigate the role of AI in the context of insurance, pension and financial inclusion, much remains unknown.

5.2.1 Insurance. Few studies investigated AI in the insurance context. Included research analyzed chatbots in supporting customer value creation (Riikkinen *et al.*, 2018), assessed managers' perspectives on chatbots (Jang *et al.*, 2021), reviewed the applicability of AI in insurance fraud detection (West and Bhattacharya, 2016) and conceptualized the role of insurance robo-advisors (Wexler and Oberlander, 2021). Various avenues for future research remain unexplored. Researchers may wish to investigate how AI can augment/replace current insurance claim systems and processes or investigate the impact of data and open-source protocols on ecosystems.

5.2.2 Financial well-being. While several researchers have investigated interventions aimed at increasing financial well-being, including education, counseling and nudging (Fernandes *et al.*, 2014), others have studied how different personal factors, such as sociodemographic factors, traits, skills or life events, affect individuals' financial well-being (Luhamnn *et al.*, 2012). Context is crucial for research on financial well-being, and as such the role of technology, such as AI, requires more attention in future research (Brüggen *et al.*, 2017). While select studies included in the review highlighted the implications of AI in enhancing financial inclusion, providing low-cost personal advice options and increased accessibility (Lee, 2020; Mhlanga, 2020), researchers could further explore how AI can be employed to improve individuals' financial capability or how consumer (financial) literacy and information asymmetry affect the adoption of AI-augmented services, such as robo-advisors or chatbots. Mogaji *et al.* (2020) examined the ethical implications, data modeling challenges and overall relationship between AI and financial services from the perspective of vulnerable consumers. Future research may wish to empirically test whether AI adoption benefits vulnerable individuals or if they might be subject to increased exclusion instead. How AI can reduce financial vulnerability, mitigate emotional distress experienced by consumers and assist in crisis management are just some of the many potential avenues for further research.

5.2.3 Pension industry. The pension industry is already adopting AI. For example, investment firm Mercer launched an AI-powered tool to assist defined benefit schemes in predicting member outcome options, support risk management and optimize member offer structures (Mercer, 2020). Retirement decision-making differs from other private investment decisions in its long-term nature and significance. Much research on retirement planning and savings can be found in the literature, but the supporting role of technology has only recently garnered research interest (Eberhardt *et al.*, 2020; Hentzen *et al.*, 2021), and research on how AI can impact the pension industry is scarce with only one study (Henkel *et al.*, 2020). Future research may wish to investigate how AI can increase pension member engagement through customer journey mapping or personalization efforts. Other topics could be members' willingness to accept AI in pension investment selection and how AI would perform in comparison to investment managers (Arli *et al.*, 2020).

5.2.4 Digital economy. One research area that has garnered limited attention to date is the role of financial institutions and services in building up and supporting the development of digital economies (Agyapong, 2021). The digital economy includes "all economic activity reliant on, or significantly enhanced through the use of digital inputs, including digital technologies, digital infrastructure, digital services, and data. It refers to all producers and consumers, including government, that are utilizing these digital inputs in their economic activities" (OECD, 2020, p. 34). By adopting a macro-environmental view of financial services and their role in the digital economy, researchers may be able to study the implications of AI in a broader, globalized context. Future research could investigate how AI can facilitate cross-country information/data exchange and management, enhance international financial fraud detection systems focusing on tax evasion or illegal offshore accounts or investigate whether AI can reduce financial cybercrime. Employees' digital skill set and organizations' digital capabilities may also warrant further investigation, as well as legal and regulatory implications of AI-implementation cross-countries.

5.2.5 Ethics, legal and policy. Research on regulation, policy, data protection and ethics should be viewed as underlying the research contexts discussed above. While numerous studies included in the review focused on regulation in the context of AI and financial services, many questions remain unanswered. For example, the studies included in our review analyzed general financial regulatory implications of AI (Wall, 2018), proposed regulatory approaches to robo-advisory (Chiu, 2019; Guo, 2020; Lightbourne, 2017) and conceptualized regulatory responsibility of credit scoring and bias reduction (Aggarwal, 2021). However, little research has attempted to answer questions related to third-party AI vendor management and its implications for consumers' financial data protection. Numerous studies have emphasized the need for ethical standards when using AI in financial services. However, the question of what constitutes ethical and socially responsible AI provision from a firm's or consumers' perspective remains open.

5.3 New research constructs and relationships

Our systematic review reveals that the literature has adopted various investigative perspectives, employing predictor variables related to technology, consumer beliefs, service experiences and firm characteristics. However, although numerous studies have applied consumer-related variables as independent, mediator, moderator or dependent variables, we identified gaps around the concepts of customer engagement and consumer financial behavior.

5.3.1 Customer engagement. To date, few studies have explicitly considered the role of AI in fostering customer engagement with financial services (for exceptions see Chiu, 2019; van Thiel and van Raaij, 2019; Xu *et al.*, 2020). It would be interesting to investigate the impact of AI on customer engagement behavior and its consequences (Pala *et al.*, 2021). Variables of interest could include consumer outcomes, such as cognitive, emotional and attitudinal behavior, and firm-related outcomes, such as competitiveness, financial and reputational consequences (van Doorn *et al.*, 2010). Furthermore, while some studies have commenced with investigations into how gamification and personalization can enhance customer engagement (Anshari *et al.*, 2019; Eisingerich *et al.*, 2019), further research is needed in the context of AI-enabled financial services regarding variables such as consumers' sense of control, progress tracking, journey mapping, rewards, nudges or prompts to facilitate engagement. Meanwhile, researchers looking to investigate the role of AI in personalization efforts may want to investigate relationships between explanatory variables, such as transparency, privacy, frequency of personalized communication, and outcome variables, such as customer loyalty, relationship quality and improved financial behaviors (Wang *et al.*, 2016).

5.3.2 Financial knowledge and behavior. Given the financial service context, surprisingly few studies analyzed the relationship between consumer financial behaviors and AI acceptance or how AI can improve consumer financial behaviors (Fulk *et al.*, 2018; Luo *et al.*, 2019). Researchers seeking to investigate AI and financial investments could thus study the relationship between consumers' risk tolerance, risk perception, perceived financial security or perceived financial uncertainty and acceptance of robo-advice (Hoffmann *et al.*, 2015; Hoffmann and Plotkina, 2020). Additionally, it would be interesting to study the impact of AI on increasing financial well-being. Explanatory variables demonstrated to affect consumer well-being include materialism, (lack of) self-control, long-term money planning (Netemeyer *et al.*, 2018), involvement, anxiety and literacy (Mende and van Doorn, 2014). How AI can reduce negative financial behaviors and support positive behaviors is also yet to be explored. One exciting avenue for future research concerns is studying the effect of AI on consumer financial literacy and information asymmetry.

5.3.3 Technology acceptance. We call for research that revisits technology acceptance through a digital marketing and communication lens (van Esch and Stewart Black, 2021). By adopting a customer-dominant logic, we suggest researchers to study the effects of branding and relationship marketing (Steinhoff *et al.*, 2019) on AI acceptance. One may also wish to delve deeper into analyzing the effect of different message types, consumer sense-making and external influences, such as competitor communication and customer-to-customer communication on AI acceptance and use (Finne and Grönroos, 2017). Lastly, researchers may wish to investigate the role of AI in enhancing and facilitating information flow, including consumer information-seeking behaviors, considering explanatory constructs, such as financial service provider created digital information, external provider and consumer co-created financial information, information avoidance and informational social support (Peltier *et al.*, 2020).

5.3.4 Conceptual propositions. Finally, future research should empirically test the proposed relationships considered in various conceptual articles (Aggarwal, 2021; Mogaji *et al.*, 2020; Payne *et al.*, 2021a; Riikkinen *et al.*, 2018; Wexler and Oberlander, 2021). For example, Payne *et al.* (2021a) propose numerous AI-service exchange antecedents, including consumer characteristics, such as risk tolerance, need for human interaction or enjoyment, or supporting institutional actor characteristics, such as AI technology infrastructure and data sharing among network actors. On the other hand, Wexler and Oberlander (2021) provide conceptualizations around robo-advisory characteristics, including trustworthiness, disembodiment, customizability and user-friendliness. Lastly, future research can further examine the framework and relationships proposed by Mogaji *et al.* (2020), by empirically testing how AI can assist financially vulnerable customers.

5.4 New data and methods

5.4.1 Methodological improvements and bias testing. Regarding studies that employed a survey-design approach, we call for methodological improvements to better account for response bias, sample selection bias and common method bias (Bickman and Rog, 2008; Podsakoff *et al.*, 2003). Only a few articles included in our review addressed common method (Adam *et al.*, 2020; Payne *et al.*, 2021b) or response bias (Bejou *et al.*, 1996). While Fulk *et al.* (2018) referred to sample selection bias, they do not go into detail as to how they attempted to mitigate it. Various methods have been proposed to detect and remedy common method variance (CMV), including procedural remedies such as (1) obtaining predictor and criterion variable measures from different sources, (2) counterbalancing question orders and (3) improving scale items. Potential statistical remedies include (1) Harman's single factor test, (2) partial correlation procedures and (3) using multiple-method factors (Podsakoff *et al.*, 2003).

5.4.2 Alternative methods. Another rich source of consumer data is comments and posts on social media and other consumer interfaces (Heinonen and Medberg, 2018). Textual analysis can be used to measure the consumer's AI-related attitudes and sentiments on a larger scale, while simultaneously mitigating biases of conventional surveys (e.g. social desirability). Data collection and analysis can be simplified using advanced text mining tools and even AI and ML algorithms, which aid in the reduction of substantive and psychometric properties of texts (Berger *et al.*, 2020; Heinonen and Medberg, 2018). While Medberg and Heinonen (2014) applied netnography to study value formation in retail banking, future research may wish to use netnography as a tool to investigate why consumers may prefer human financial advisors over robo-advisors, combine netnography with other data collection methods or adopt a longitudinal approach to netnography.

5.4.3 Longitudinal research design. Our review shows that with a single exception (Shanmuganathan, 2020), no study adopted a longitudinal approach. However, several authors recognize the need for longitudinal research, highlighting avenues for further research. Researchers may want to track consumers wishing to use robo-advisors over a longer period to investigate how consumer resources and help-seeking behaviors may impact robo-advisory adoption (Fulk *et al.*, 2018). Adam *et al.* (2020) suggest adopting a longitudinal design to measure whether consumers get used to chatbots over time and whether firm–consumer relationships may degrade due to the nature of self-service channels.

5.4.4 Meta-analyses. Lastly, this review identifies the need for a meta-analysis. While there are some recent meta-analyses on AI in the accounting and finance (Singh *et al.*, 2021b) or investment context (von Stumm and Ackermann, 2013), we encourage studies to conduct meta-analyses from a consumer or organizational point of view on trust in or acceptance of robo-advisors and AI adoption in banking (Arli *et al.*, 2020).

References

Abdelazim, H.Y. and Wahba, K. (2006), "An artificial intelligence approach to portfolio selection and management", *International Journal of Financial Services Management*, Vol. 1 Nos 2-3, pp. 243-254.

Abdulquadri, A., Mogaji, E., Kieu, T.A. and Nguyen, N.P. (2021), "Digital transformation in financial services provision: a Nigerian perspective to the adoption of chatbot", *Journal of Enterprising Communities: People and Places in the Global Economy*, Vol. 15 No. 2, pp. 258-281.

Abellán, J. and Castellano, J.G. (2017), "A comparative study on base classifiers in ensemble methods for credit scoring", *Expert Systems with Applications*, Vol. 73, pp. 1-10.

Accenture (2019), "The cost of cybercrime", available at: https://www.accenture.com/_acnmedia/PDF-96/Accenture-2019-Cost-of-Cybercrime-Study-Final.pdf.

Acharya, A. and Arnold, Z. (2019), "Chinese public AI R&D spending: provisional findings", available at: https://cset.georgetown.edu/publication/chinese-public-ai-rd-spending-provisional-findings/.

Adam, M., Wessel, M. and Benlian, A. (2020), "AI-based chatbots in customer service and their effects on user compliance", *Electronic Markets*, Vol. 31 No. 2, pp. 427-445.

Aggarwal, N. (2021), "The norms of algorithmic credit scoring", *Cambridge Law Journal*, Vol. 80 No. 1, pp. 42-73.

Agyapong, D. (2021), "Implications of digital economy for financial institutions in Ghana: an exploratory inquiry", *Transnational Corporations Review*, Vol. 13 No. 1, pp. 51-61.

Ala'raj, M. and Abbod, M.F. (2016), "Classifiers consensus system approach for credit scoring", *Knowledge-Based Systems*, Vol. 104, pp. 89-105.

Ali, O., Ally, M., Clutterbuck and Dwivedi, Y.K. (2020), "The state of play of blockchain technology in the financial services sector: a systematic literature review", *International Journal of Information Management*, Vol. 54 (forthcoming).

Aloud, M.E. (2018), "Investment opportunities forecasting: a genetic programming-based dynamic portfolio trading system under a directional-change framework", *Journal of Computational Finance*, Vol. 22 No. 1, pp. 1-35.

Anshari, M., Almunawar, M.N., Lim, S.A. and Al-Mudimigh, A. (2019), "Customer relationship management and big data enabled: personalization and customization of services", *Applied Computing and Informatics*, Vol. 15 No. 2, pp. 94-101.

Arli, D., van Esch, P., Bakpayev, M. and Laurence, A. (2020), "Do consumers really trust cryptocurrencies?", *Marketing Intelligence and Planning*, Vol. 39 No. 1, pp. 74-90.

Ashta, A. and Herrmann, H. (2021), "Artificial intelligence and Fintech: an overview of opportunities and risks for banking, investments, and microfinance", *Strategic Change*, Vol. 30 No. 3, pp. 211-222.

Asuncion, A. and Newman, D. (2007), "UCI machine learning repository", available at: http://www.ics.uci.edu/~mlearn/MLRepository.html.

Atwal, G. and Bryson, D. (2021), "Antecedents of intention to adopt artificial intelligence services by consumers in personal financial investing", *Strategic Change*, Vol. 30 No. 3, pp. 293-298.

Baghdasaryan, V., Davtyan, H., Grigoryan, A. and Khachatryan, K. (2021), "Comparison of econometric and deep learning approaches for credit default classification", *Strategic Change*, Vol. 30 No. 3, pp. 257-268.

Bai, Z. (2021), "Does Robo-advisory help reduce the likelihood of carrying a credit card debt? Evidence from an instrumental variable approach", *Journal of Behavioral and Experimental Finance*, Vol. 29 (forthcoming).

Baiocchi, G., Graizbord, D. and Rodríguez-Muñiz, M. (2013), "Actor-network theory and the ethnographic imagination: an exercise in translation", *Qualitative Sociology*, Vol. 36 No. 4, pp. 323-341.

Balyone, T.J.B. (2019), "Theorising effective uses of digital technology with activity theory", *Technology, Pedagogy and Education*, Vol. 28 No. 4, pp. 447-462.

Baron, R.M. and Kenny, D.A. (1986), "The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations", *Journal of Personality and Social Psychology*, Vol. 51 No. 6, pp. 1173-1182.

Bejou, D., Wray, B. and Ingram, T.N. (1996), "Determinants of relationship quality: an artificial neural network analysis", *Journal of Business Research*, Vol. 36, pp. 137-143.

Belanche, D., Casaló, L.V. and Flavián, C. (2019), "Artificial Intelligence in FinTech: understanding Robo-advisors adoption among customers", *Industrial Management and Data Systems*, Vol. 119 No. 7, pp. 1411-1430.

Berger, J., Humphreys, A., Ludwig, S., Moe, W.W., Netzer, O. and Schweidel, D.A. (2020), "Uniting the tribes: using text for marketing insight", *Journal of Marketing*, Vol. 84 No. 1, pp. 1-25.

Bhatia, A., Chandani, A. and Chhateja, J. (2020), "Robo advisory and its potential in addressing the behavioral biases of investors - a qualitative study in Indian context", *Journal of Behavioral and Experimental Finance*, Vol. 25 (forthcoming).

Bhatore, S., Mohan, L. and Reddy, Y.R. (2020), "Machine learning techniques for credit risk evaluation: a systematic literature review", *Journal of Banking and Financial Technology*, Vol. 4 No. 1, pp. 111-138.

Bickman, L. and Rog, D.J. (2008), *The SAGE Handbook of Applied Social Research Methods*, SAGE Publications, Los Angeles.

Borgogno, O. and Colangelo, G. (2019), "Data sharing and interoperability: fostering innovation and competition through APIs", *Computer Law and Security Review*, Vol. 35 No. 5.

Boustani, N.M. (2021), "Artificial intelligence impact on banks clients and employees in an Asian developing country", *Journal of Asia Business Studies* (forthcoming).

Brenner, L. and Meyll, T. (2020), "Robo-advisors: a substitute for human financial advice?", *Journal of Behavioral and Experimental Finance*, Vol. 25 (forthcoming).

Brüggen, E.C., Hogreve, J., Holmlund, M., Kabadayi, S. and Löfgren, M. (2017), "Financial well-being: a conceptualization and research agenda", *Journal of Business Research*, Vol. 79, pp. 228-237.

Buchanan, B. (2019), "Artificial intelligence in finance", available at: https://www.turing.ac.uk/research/publications/artificial-intelligence-finance.

Buitrago, R.E. and Barbosa Camargo, M.I. (2021), "Institutions, institutional quality, and international competitiveness: review and examination of future research directions", *Journal of Business Research*, Vol. 128, pp. 423-435.

Campesato, O. (2020), *Artificial Intelligence, Machine Learning, and Deep Learning*, Mercury Learning & Information, Dulles, Virginia.

Castillo, D., Canhoto, A.I. and Said, E. (2020), "The dark side of AI-powered service interactions: exploring the process of co-destruction from the customer perspective", *Service Industries Journal*, Vol. 41 Nos 13-14, pp. 900-925.

Cavalcante, R.C., Brasileiro, R.C., Souza, V.L.F., Nobrega, J.P. and Oliveira, A.L.I. (2016), "Computational intelligence and financial markets: a survey and future directions", *Expert Systems with Applications*, Vol. 55, pp. 194-211.

Chan, C., Chow, D.C., Wong, J., Dimakis, N., Nayler, D., Bermudes, J. and Baker, M. (2019), "Artificial intelligence applications in financial services", available at: https://www.oliverwyman.com/our-expertise/insights/2019/dec/artificial-intelligence-applications-in-financial-services.html.

Chen, Y., Mandler, T. and Meyer-Waarden, L. (2021), "Three decades of research on loyalty programs: a literature review and future research agenda", *Journal of Business Research*, Vol. 124, pp. 179-197.

Chiu, I.H. (2019), "Transforming the financial advice market-the roles of Robo-advice, financial regulation and public governance in the United Kingdom", *Banking and Finance Law Review*, Vol. 35 No. 1, pp. 9-35.

Citi Group (2018), "Bank of the future: the ABCs of digital disruption in finance", available at: http://www.smallake.kr/wp-content/uploads/2018/05/AHDX6.pdf.

Correa Bahnsen, A., Aouada, D., Stojanovic, A. and Ottersten, B. (2016), "Feature engineering strategies for credit card fraud detection", *Expert Systems with Applications*, Vol. 51, pp. 134-142.

Cubric, M. (2020), "Drivers, barriers and social considerations for AI adoption in business and management: a tertiary study", *Technology in Society*, Vol. 62 (forthcoming).

Dastile, X., Celik, T. and Potsane, M. (2020), "Statistical and machine learning models in credit scoring: a systematic literature survey", *Applied Soft Computing*, Vol. 91.

Davenport, T., Guha, A., Grewal, D. and Bressgott, T. (2020), "How artificial intelligence will change the future of marketing", *Journal of the Academy of Marketing Science*, Vol. 48 No. 1, pp. 24-42.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical models", *Management Science*, Vol. 35 No. 8, pp. 982-1003.

Davis, J., Mengersen, K., Bennett, S. and Mazerolle, L. (2014), "Viewing systematic reviews and meta-analysis in social research through different lenses", *SpringerPlus*, Vol. 3 No. 511, pp. 1-9.

Deloitte (2018), "The new physics of financial services: how artificial intelligence is transforming the financial ecosystem", available at: https://www2.deloitte.com/au/en/pages/financial-services/articles/artificial-intelligence-transforming-financial-ecosystem.html.

Eberhardt, W., Brüggen, E., Post, T. and Hoet, C. (2020), "Engagement behavior and financial well-being: the effect of message framing in online pension communication", *International Journal of Research in Marketing*, Vol. 38 No. 2, pp. 448-471.

Eisingerich, A.B., Marchand, A., Fritze, M.P. and Dong, L. (2019), "Hook vs hope: how to enhance customer engagement through gamification", *International Journal of Research in Marketing*, Vol. 36 No. 2, pp. 200-215.

Elragal, A. and Klischewski, R. (2017), "Theory-driven or process-driven prediction? Epistemological challenges of big data analytics", *Journal of Big Data*, Vol. 4 No. 19, pp. 1-20.

Eren, B.A. (2021), "Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey", *International Journal of Bank Marketing*, Vol. 39 No. 2, pp. 294-311.

European Commission (2020), "Germany AI strategy report. AI watch: monitor the development, uptake and impact of artificial intelligence for Europe", available at: https://knowledge4policy.ec.europa.eu/ai-watch/germany-ai-strategy-report_en.

Fernández-Olit, B., Martín Martín, J.M. and Porras González, E. (2019), "Systematized literature review on financial inclusion and exclusion in developed countries", *International Journal of Bank Marketing*, Vol. 38 No. 3, pp. 600-626.

Fernandes, T. and Oliveira, E. (2021), "Understanding consumers' acceptance of automated technologies in service encounters: drivers of digital voice assistants adoption", *Journal of Business Research*, Vol. 122, pp. 180-191.

Fernandes, D., Lynch, J.G. and Netemeyer, R.G. (2014), "Financial literacy, financial education, and downstream financial behaviors", *Management Science*, Vol. 60 No. 8, pp. 1861-1883.

Finne, Å. and Grönroos, C. (2017), "Communication-in-use: customer-integrated marketing communication", *European Journal of Marketing*, Vol. 51 No. 3, pp. 445-463.

Flavián, C., Pérez-Rueda, A., Belanche, D. and Casaló, L.V. (2021), "Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness", *Journal of Service Management* (forthcoming).

Fossey, E., Harvey, C., McDermott, F. and Davidson, L. (2002), "Understanding and evaluating qualitative research", *Australian and New Zealand Journal of Psychiatry*, Vol. 36 No. 6, pp. 717-732.

Fulk, M., Grable, J.E., Watkins, K. and Kruger, M. (2018), "Who uses Robo-advisory services, and who does not?", *Financial Services Review*, Vol. 27, pp. 173-188.

Gallego-Gomez, C. and De-Pablos-Heredero, C. (2020), "Artificial intelligence as an enabling tool for the development of dynamic capabilities in the banking industry", *International Journal of Enterprise Information Systems*, Vol. 16 No. 3, pp. 20-33.

Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013), "Seeking qualitative rigor in inductive research", *Organizational Research Methods*, Vol. 16 No. 1, pp. 15-31.

Guo, L. (2020), "Regulating investment robo-advisors in China: problems and prospects", *European Business Organization Law Review*, Vol. 21 No. 1, pp. 69-99.

Haenlein, M. and Kaplan, A. (2019), "A brief history of artificial intelligence: on the past, present, and future of artificial intelligence", *California Management Review*, Vol. 61 No. 4, pp. 5-14.

Heinonen, K. and Medberg, G. (2018), "Netnography as a tool for understanding customers: implications for service research and practice", *Journal of Services Marketing*, Vol. 32 No. 6, pp. 657-679.

Heinonen, K. and Strandvik, T. (2015), "Customer-dominant logic: foundations and implications", *Journal of Services Marketing*, Vol. 29 Nos 6/7, pp. 472-484.

Heinonen, K., Stauss, B., Strandvik, T., Mickelsson, K.J., Edvardsson, B., Sundström, E. and Andersson, P. (2010), "A customer-dominant logic of service", *Journal of Service Management*, Vol. 21 No. 4, pp. 531-548.

Henkel, A.P., Bromuri, S., Iren, D. and Urovi, V. (2020), "Half human, half machine–augmenting service employees with AI for interpersonal emotion regulation", *Journal of Service Management*, Vol. 31 No. 2, pp. 247-265.

Hentzen, J.K., Hoffmann, A.O.I. and Dolan, R.M. (2021), "Which consumers are more likely to adopt a retirement app and how does it explain mobile technology-enabled retirement engagement?", *International Journal of Consumer Studies* (forthcoming).

Hildebrand, C. and Bergner, A. (2020), "Conversational Robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making", *Journal of the Academy of Marketing Science*, Vol. 49 No. 4, pp. 659-676.

Hoffmann, A.O.I. and Plotkina, D. (2020), "Why and when does financial information affect retirement planning intentions and which consumers are more likely to act on them?", *Journal of Business Research*, Vol. 117, pp. 411-431.

Hoffmann, A., Post, T. and Pennings, J.M.E. (2015), "How investor perceptions drive actual trading and risk-taking behavior", *Journal of Behavioral Finance*, Vol. 16, pp. 94-103.

Huang, J.C. and Pan, W.T. (2010), "Forecasting classification of operating performance of enterprises by probabilistic neural network", *Journal of Information and Optimization Sciences*, Vol. 31 No. 2, pp. 333-345.

Huang, B. and Philp, M. (2020), "When AI-based services fail: examining the effect of the self-AI connection on willingness to share negative word-of-mouth after service failures", *The Service Industries Journal*, Vol. 41 Nos 13-14, pp. 877-899.

Huang, M.-H. and Rust, R.T. (2018), "Artificial intelligence in service", *Journal of Service Research*, Vol. 21 No. 2, pp. 155-172.

Hunt, S.D. (2010), *Marketing Theory: Foundations, Controversy, Strategy, Resource-Advantage Theory*, Routledge, Oxfordshire.

Hunt, S.D. (2018), "Advancing marketing strategy in the marketing discipline and beyond: from promise, to neglect, to prominence, to fragment (to promise?)", *Journal of Marketing Management*, Vol. 34 Nos 1-2, pp. 16-51.

Iiie, M., Moraru, A.D. and Ghita-Mitrescu, S. (2017), "The hierarchical determination of customer satisfaction with banking services using an artificial Neural Network", *Transformations in Business and Economics*, Vol. 16 No. 2A, pp. 401-420.

Jakšič, M. and Marinč, M. (2019), "Relationship banking and information technology: the role of artificial intelligence and FinTech", *Risk Management*, Vol. 21 No. 1, pp. 1-18.

Jang, M., Jung, Y. and Kim, S. (2021), "Investigating managers' understanding of chatbots in the Korean financial industry", *Computers in Human Behavior*, Vol. 120 (forthcoming).

Jung, D., Dorner, V., Weinhardt, C. and Pusmaz, H. (2018), "Designing a Robo-advisor for risk-averse, low-budget consumers", *Electronic Markets*, Vol. 28 No. 3, pp. 367-380.

Kahiya, E.T. (2018), "Five decades of research on export barriers: review and future directions", *International Business Review*, Vol. 27 No. 6, pp. 11725-11188.

Kapoor, S. and Bisht, A. (2020), "Asia/Pacific financial services: artificial intelligence market forecast, 2020-2024", available at: https://www.idc.com/getdoc.jsp?containerId=AP46522820.

Kapsis, I. (2020), "A truly future-oriented legal framework for Fintech in the EU", *European Business Law Review*, Vol. 31 No. 3, pp. 475-514.

Karanasios, S., Nardi, B., Spinuzzi, C. and Malaurent, J. (2021), "Moving forward with activity theory in a digital world", *Mind, Culture, and Activity*.

Kaur, N., Sahdev, S.L., Sharma, M. and Siddiqui, L. (2020), "Banking 4.0: 'the influence of artificial intelligence on the banking industry and how AI is changing the face of modern day banks'", *International Journal of Management*, Vol. 11 No. 6, pp. 577-585.

Khandani, A.E., Kim, A.J. and Lo, A.W. (2010), "Consumer credit-risk models via machine-learning algorithms", *Journal of Banking and Finance*, Vol. 34 No. 11, pp. 2767-2787.

Khemakhem, S., Ben Said, F. and Boujelbene, Y. (2018), "Credit risk assessment for unbalanced datasets based on data mining, artificial neural network and support vector machines", *Journal of Modelling in Management*, Vol. 13 No. 4, pp. 932-951.

Konigstorfer, F. and Thalmann, S. (2020), "Applications of Artificial Intelligence in commercial banks - a research agenda for behavioral finance", *Journal of Behavioral and Experimental Finance*, Vol. 27 (forthcoming).

Koutanaei, F.N., Sajedi, H. and Khanbabaei, M. (2015), "A hybrid data mining model of feature selection algorithms and ensemble learning classifiers for credit scoring", *Journal of Retailing and Consumer Services*, Vol. 27, pp. 11-23.

Kraus, M. and Feuerriegel, S. (2017), "Decision support from financial disclosures with deep neural networks and transfer learning", *Decision Support Systems*, Vol. 104, pp. 38-48.

Krishen, A.S., Dwivedi, Y.K., Bindu, N. and Kumar, K.S. (2021), "A broad overview of interactive digital marketing: a bibliometric network analysis", *Journal of Business Research*, Vol. 131, pp. 183-195.

Kruppa, J., Schwarz, A., Arminger, G. and Ziegler, A. (2013), "Consumer credit risk: individual probability estimates using machine learning", *Expert Systems with Applications*, Vol. 40 No. 13, pp. 5125-5131.

Kumar, K.N. and Balaramachandran, P.R. (2018), "Robotic process automation- A study of the impact on customer experience in retail banking industry", *Journal of Internet Banking and Commerce*, Vol. 23 No. 3, pp. 1-27.

Kumar, S., Tomar, S. and Verma, D. (2019), "Women's financial planning for retirement", *International Journal of Bank Marketing*, Vol. 37 No. 1, pp. 120-141.

Ładyżyński, P., Żbikowski, K. and Gawrysiak, P. (2019), "Direct marketing campaigns in retail banking with the use of deep learning and random forests", *Expert Systems with Applications*, Vol. 134, pp. 28-35.

Larivière, B., Bowen, D., Andreassen, T.W., Kunz, W., Sirianni, N.J., Voss, C. and De Keyser, A. (2017), "'Service Encounter 2.0': an investigation into the roles of technology, employees and customers", *Journal of Business Research*, Vol. 79, pp. 238-246.

Latour, B. (1987), *Science in Action: How to Follow Scientists and Engineers through Society*, Harvard University Press, Cambridge, MA.

Lee, J. (2020), "Access to finance for artificial intelligence regulation in the financial services industry", *European Business Organization Law Review*, Vol. 21 No. 4, pp. 731-757.

Lee, I. and Shin, Y.J. (2020), "Machine learning for enterprises: applications, algorithm selection, and challenges", *Business Horizons*, Vol. 63 No. 2, pp. 157-170.

Leung, M.T., Chen, A.S. and Mancha, R. (2009), "Making trading decisions for financial-engineered derivatives: a novel ensemble of neural networks using information content", *Intelligent Systems in Accounting Finance and Management*, Vol. 16 No. 4, pp. 257-277.

Lightbourne, J. (2017), "Algorithms and fiduciaries: existing and proposed regulatory approaches to artificially intelligent financial planners", *Duke Law Journal*, Vol. 67 No. 3, pp. 651-679.

Lim, W.M., Yap, S.F. and Makkar, M. (2021), "Home sharing in marketing and tourism at a tipping point: what do we know, how do we know, and where should we be heading?", *Journal of Business Research*, Vol. 122, pp. 534-566.

Lu, X.Y., Chu, X.Q., Chen, M.H., Chang, P.C. and Chen, S.H. (2016), "Artificial immune network with feature selection for bank term deposit recommendation", *Journal of Intelligent Information Systems*, Vol. 47 No. 2, pp. 267-285.

Luhamnn, M., Hofmann, W., Eid, M. and Lucas, R.E. (2012), "Subjective well-being and adaptation to life events: a meta-analysis", *Journal of Personality and Social Psychology*, Vol. 102 No. 3, pp. 592-615.

Lui, A. and Lamb, G.W. (2018), "Artificial intelligence and augmented intelligence collaboration: regaining trust and confidence in the financial sector", *Information and Communications Technology Law*, Vol. 27 No. 3, pp. 267-283.

Luo, X., Tong, S., Fang, Z. and Qu, Z. (2019), "Frontiers: machines vs humans: the impact of artificial intelligence chatbot disclosure on customer purchases", *Marketing Science*, Vol. 38 No. 6, pp. 937-947.

Lusch, R.F. and Nambisan, S. (2015), "Service innovation: a service-dominant logic perspective", *MIS Quarterly*, Vol. 39 No. 1, pp. 155-176.

Maass, W., Parsons, J., Purao, S., Storey, V.C. and Woo, C. (2018), "Data-driven meets theory-driven research in the era of big data: opportunities and challenges for information systems research", *Journal of the Association for Information Systems*, Vol. 19 No. 12, pp. 1253-1273.

MacInnis, D.J. (2011), "A framework for conceptual contributions in marketing", *Journal of Marketing*, Vol. 75 No. 4, pp. 136-154.

Mandler, T., Sezen, B., Chen, J. and Özsomer, A. (2021), "Performance consequences of marketing standardization/adaptation: a systematic literature review and future research agenda", *Journal of Business Research*, Vol. 125, pp. 416-435.

Markowitz, H. (1959), *Portfolio Selection: Efficient Diversification of Investments*, Wiley, New York.

McKinsey & Company (2020), "AI-bank of the future: can banks meet the AI challenge?", available at: https://www.mckinsey.com/industries/financial-services/our-insights/ai-bank-of-the-future-can-banks-meet-the-ai-challenge.

Medberg, G. and Heinonen, K. (2014), "Invisible value formation: a netnography in retail banking", *International Journal of Bank Marketing*, Vol. 32 No. 6, pp. 590-607.

Mende, M. and van Doorn, J. (2014), "Coproduction of transformative services as a pathway to improved consumer well-being", *Journal of Service Research*, Vol. 18 No. 3, pp. 351-368.

Mercer (2020), "Mercer launches industry first AI powered tool to predict outcome of member options exercises", available at: https://www.uk.mercer.com/newsroom/Mercer-launches-industry-first-AI-powered-tool-to-predict-outcome-of-member-options-exercises.html.

Mhlanga, D. (2020), "Industry 4.0 in finance: the impact of artificial intelligence (AI) on digital financial inclusion", *International Journal of Financial Studies*, Vol. 8 No. 3, pp. 1-14.

Mhlanga, D. (2021), "Financial inclusion in emerging economies: the application of machine learning and artificial intelligence in credit risk assessment", *International Journal of Financial Studies*, Vol. 9 No. 3, pp. 1-16.

Milana, C. and Ashta, A. (2021), "Artificial intelligence techniques in finance and financial markets: a survey of the literature", *Strategic Change*, Vol. 30 No. 3, pp. 189-209.

Mogaji, E., Balakrishnan, J., Nwoba, A.C. and Nguyen, N.P. (2021), "Emerging-market consumers' interactions with banking chatbots", *Telematics and Informatics*, Vol. 65 (forthcoming).

Mogaji, E., Soetan, T.O. and Kieu, T.A. (2020), "The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers", *Australasian Marketing Journal* (forthcoming).

Mor, S. and Gupta, G. (2021), "Artificial intelligence and technical efficiency: the case of Indian commercial banks", *Strategic Change*, Vol. 30 No. 3, pp. 235-245.

Moscato, V., Picariello, A. and Sperlí, G. (2021), "A benchmark of machine learning approaches for credit score prediction", *Expert Systems with Applications*, Vol. 165 (forthcoming).

Mosteanu, N.R. (2019), "International financial markets face to face with artificial intelligence and digital era", *Theoretical and Applied Economics*, Vol. 26 No. 3, pp. 123-134.

Nehemia-Maletzky, M., Iyamu, T. and Shaanika, I. (2018), "The use of activity theory and actor network theory as lenses to underpin information systems studies", *Journal of Systems and Information Technology and People*, Vol. 20 No. 2, pp. 191-206.

Netemeyer, R.G., Warmath, D., Fernandes, D., Lynch, J.G., Fischer, E. and Toubia, O. (2018), "How am I doing? Perceived financial well-being, its potential antecedents, and its relation to overall well-being", *Journal of Consumer Research*, Vol. 45 No. 1, pp. 68-89.

OECD (2020), "A roadmap toward a common framework for measuring the digital economy", available at: https://www.oecd.org/going-digital/topics/measurement/.

Pala, E., Kapitan, S. and van Esch, P. (2021), "Simulated satiation through reality-enhancing technology", *Psychology and Marketing* (forthcoming).

Paleologo, G., Elisseeff, A. and Antonini, G. (2010), "Subagging for credit scoring models", *European Journal of Operational Research*, Vol. 201 No. 2, pp. 490-499.

Paul, J. and Benito, G.R.G. (2018), "A review of research on outward foreign direct investment from emerging countries, including China: what do we know, how do we know and where should we be heading?", *Asia Pacific Business Review*, Vol. 24 No. 1, pp. 90-115.

Paul, J. and Criado, A.R. (2020), "The art of writing literature review: what do we know and what do we need to know?", *International Business Review*, Vol. 29 (forthcoming).

Paul, J. and Rosado-Serrano, A. (2019), "Gradual Internationalization vs Born-Global/International new venture models", *International Marketing Review*, Vol. 36 No. 6, pp. 830-858.

Paul, J., Parthasarathy, S. and Gupta, P. (2017), "Exporting challenges of SMEs: a review and future research agenda", *Journal of World Business*, Vol. 52 No. 3, pp. 327-342.

Paul, J., Lim, W.M., O'Cass, A., Hao, A.W. and Bresciani, S. (2021a), "Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR)", *International Journal of Consumer Studies*, Vol. 45 No. 4 (forthcoming).

Paul, J., Merchant, A., Dwivedi, Y.K. and Rose, G. (2021b), "Writing an impactful review article: what do we know and what do we need to know?", *Journal of Business Research*, Vol. 133, pp. 337-340.

Payne, E.H.M., Peltier, J.W. and Barger, V.A. (2018), "Mobile banking and AI-enabled mobile banking: the differential effects of technological and non-technological factors on digital natives' perceptions and behavior", *Journal of Research in Interactive Marketing*, Vol. 12 No. 3, pp. 328-346.

Payne, E.H.M., Dahl, A.J. and Peltier, J.W. (2021a), "Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems", *Journal of Research in Interactive Marketing*, Vol. 15 No. 2, pp. 200-222.

Payne, E.H.M., Peltier, J. and Barger, V.A. (2021b), "Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms", *Journal of Research in Interactive Marketing*, Vol. 15 No. 1, pp. 68-85.

Peltier, J.W., Dahl, A.J. and Swan, E.L. (2020), "Digital information flows across a B2C/C2C continuum and technological innovations in service ecosystems: a service-dominant logic perspective", *Journal of Business Research*, Vol. 121, pp. 724-734.

Pemer, F. (2020), "Enacting professional service work in times of digitalization and potential disruption", *Journal of Service Research*, Vol. 24 No. 2, pp. 249-268.

Philip, D.J., Sudarsanam, N. and Ravindran, B. (2018), "Improved insights on financial health through partially constrained Hidden Markov Model clustering on loan repayment data", *Data Base For Advances In Information Systems*, Vol. 49 No. 3, pp. 98-113.

Piris, Y. and Gay, A.C. (2021), "Customer satisfaction and natural language processing", *Journal of Business Research*, Vol. 124, pp. 264-271.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903.

Punniyamoorthy, M. and Sridevi, P. (2016), "Identification of a standard AI based technique for credit risk analysis", *Benchmarking*, Vol. 23 No. 5, pp. 1381-1390.

PWC (2017), "Sizing the prize-What's the real value of AI for your business and how can you capitalise?", available at: https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf.

Ramanathan, V. and Wechsler, H. (2013), "Phishing detection and impersonated entity discovery using conditional random field and latent Dirichlet allocation", *Computers and Security*, Vol. 34, pp. 123-139.

Rasiwala, F.S. and Kohl, B. (2021), "Artificial intelligence in Fintech: understanding stakeholders perception on innovation, disruption, and transformation in finance", *International Journal of Business Intelligence Research*, Vol. 12 No. 1, pp. 48-65.

Riikkinen, M., Saarijärvi, H., Sarlin, P. and Lähteenmäki, I. (2018), "Using artificial intelligence to create value in insurance", *International Journal of Bank Marketing*, Vol. 36 No. 6, pp. 1145-1168.

Rogers, E.M. (1995), *Diffusion of Innovations*, Free Press, New York, NY.

Russell, S.J. and Norvig, P. (2010), *Artificial Intelligence: A Modern Approach*, 3rd ed., Pearson, Essex.

Sandstrom, S., Edvardsson, B., Kristensson, P. and Magnusson, P. (2008), "Value in use through service experience", *Managing Service Quality*, Vol. 18 No. 2, pp. 112-126.

Schlinger, H.D. (2003), "The myth of intelligence", *The Psychological Record*, Vol. 53 No. 1, pp. 15-32.

Seiler, V. and Fanenbruck, K.M. (2021), "Acceptance of digital investment solutions: the case of Robo advisory in Germany", *Research in International Business and Finance*, Vol. 58 (forthcoming).

Shanmuganathan, M. (2020), "Behavioural finance in an era of artificial intelligence: longitudinal case study of Robo-advisors in investment decisions", *Journal of Behavioral and Experimental Finance*, Vol. 27 (forthcoming).

Singh, I., Kumar, N., Srinivasa, K.G., Maini, S., Ahuja, U. and Jain, S. (2021a), "A multi-level classification and modified PSO clustering based ensemble approach for credit scoring", *Applied Soft Computing*, Vol. 111 (forthcoming).

Singh, N.P., Som, B.K., Komalavalli, C. and Goel, H. (2021b), "A meta-analysis of the application of artificial neural networks in accounting and finance", *SCMS Journal of Indian Management*, Vol. 18 No. 1, pp. 5-21.

Snyder, H. (2019), "Literature review as a research methodology: an overview and guidelines", *Journal of Business Research*, Vol. 104, pp. 333-339.

Srivastava, S., Singh, S. and Dhir, S. (2020), "Culture and International business research: a review and research agenda", *International Business Review*, Vol. 29 (forthcoming).

Steinhoff, L., Arli, D., Weaven, S. and Kozlenkova, I.V. (2019), "Online relationship marketing", *Journal of the Academy of Marketing Science*, Vol. 47, pp. 369-393.

Sterne, J. (2017), *Artificial Intelligence for Marketing : Practical Applications*, John Wiley & Sons, New Jersey.

Suhartanto, D., Syarief, M.E., Chandra Nugraha, A., Suhaeni, T., Masthura, A. and Amin, H. (2021), "Millennial loyalty towards artificial intelligence-enabled mobile banking. Evidence from Indonesian Islamic banks", *Journal of Islamic Marketing* (forthcoming).

Sun, T. and Vasarhelyi, M.A. (2018), "Predicting credit card delinquencies: an application of deep neural networks", *Intelligent Systems in Accounting, Finance and Management*, Vol. 25 No. 4, pp. 174-189.

Tokic, D. (2018), "BlackRock Robo-Advisor 4.0: when artificial intelligence replaces human discretion", *Strategic Change*, Vol. 27 No. 4, pp. 285-290.

Trivedi, J. (2019), "Examining the customer experience of using banking chatbots and its impact on brand love: the moderating role of perceived risk", *Journal of Internet Commerce*, Vol. 18 No. 1, pp. 91-111.

Truby, J. (2020), "Governing artificial intelligence to benefit the UN sustainable development goals", *Sustainable Development*, Vol. 28 No. 4, pp. 946-959.

Truby, J., Brown, R. and Dahdal, A. (2020), "Banking on AI: mandating a proactive approach to AI regulation in the financial sector", *Law and Financial Markets Review*, Vol. 14 No. 2, pp. 110-120.

Tubadji, A., Denney, T. and Webber, D.J. (2021), "Cultural relativity in consumers' rates of adoption of artificial intelligence", *Economic Inquiry*, Vol. 59 No. 3, pp. 1234-1251.

van Doorn, J., Lemon, K.N., Mittal, V., Nass, S., Pick, D., Pirner, P. and Verhoef, P.C. (2010), "Customer engagement behavior: theoretical foundations and research directions", *Journal of Service Research*, Vol. 13 No. 3, pp. 253-266.

van Doorn, J., Mende, M., Noble, S.M., Hulland, J., Ostrom, A.L., Grewal, D. and Petersen, J.A. (2016), "Domo arigato Mr. Roboto: emergence of automated social presence in organizational frontlines and customers' service experiences", *Journal of Service Research*, Vol. 20 No. 1, pp. 43-58.

van Esch, P., Arli, D. and Gheshlaghi, M.H. (2020), "Creating an effective self-managed service climate for frontline service employees", *Journal of Retailing and Consumer Services*, Vol. 57 (forthcoming).

van Esch, P. and Cui, Y. (2021), "Does consumer promiscuity influence purchase intent? The role of artificial intelligence (AI), change seeking, and pride", *Journal of the Association for Consumer Research*, Vol. 6 No. 3, pp. 394-401.

van Esch, P. and Stewart Black, J. (2021), "Artificial intelligence (AI): revolutionizing digital marketing", *Australasian Marketing Journal*, Vol. 29 No. 3, pp. 199-203.

van Thiel, D. and van Raaij, W.F.F. (2019), "Artificial intelligence credit risk prediction: an empirical study of analytical artificial intelligence tools for credit risk prediction in a digital era", *Journal of Risk Management in Financial Institutions*, Vol. 12 No. 3, pp. 268-286.

Vargo, S.L. and Lusch, R.F. (2004), "Evolving to a new dominant logic for marketing", *Journal of Marketing*, Vol. 68 No. 1, pp. 1-17.

Vargo, S.L. and Lusch, R.F. (2008), "Service-dominant logic: continuing the evolution", *Journal of the Academy of Marketing Science*, Vol. 36 No. 1, pp. 1-10.

Vargo, S.L. and Lusch, R.F. (2017), "Service-dominant logic 2025", *International Journal of Research in Marketing*, Vol. 34 No. 1, pp. 46-67.

Vlačić, B., Corbo, L., Costa e Silva, S. and Dabić, M. (2021), "The evolving role of artificial intelligence in Marketing: a review and research agenda", *Journal of Business Research*, Vol. 128, pp. 187-203.

von Stumm, S. and Ackermann, P.L. (2013), "Investment and intellect: a review and meta-analysis", *Psychological Bulletin*, Vol. 139 No. 4, pp. 841-869.

Wall, L.D. (2018), "Some financial regulatory implications of artificial intelligence", *Journal of Economics and Business*, Vol. 100, pp. 55-63.

Wang, M., Cho, S. and Denton, T. (2016), "The impact of personalization and compatibility with past experience on e-banking usage", *International Journal of Bank Marketing*, Vol. 35 No. 1, pp. 45-55.

West, J. and Bhattacharya, M. (2016), "Intelligent financial fraud detection: a comprehensive review", *Computers and Security*, Vol. 57, pp. 47-66.

Wexler, M.N. and Oberlander, J. (2021), "Robo-advisors (RAs): the programmed self-service market for professional advice", *Journal of Service Theory and Practice*, Vol. 31 No. 3, pp. 351-365.

Xu, Y., Shieh, C.-H., van Esch, P. and Ling, I.-L. (2020), "AI customer service: task complexity, problem-solving ability, and usage intention", *Australasian Marketing Journal*, Vol. 28 No. 4, pp. 189-199.

Yu, L., Wang, S. and Lai, K.K. (2009), “An intelligent-agent-based fuzzy group decision making model for financial multicriteria decision support: the case of credit scoring”, *European Journal of Operational Research*, Vol. 195 No. 3, pp. 942-959.

Zeinalizadeh, N., Shojaie, A.A. and Shariatmadari, M. (2015), “Modeling and analysis of bank customer satisfaction using neural networks approach”, *International Journal of Bank Marketing*, Vol. 33 No. 6, pp. 717-732.

Zhang, W., He, H. and Zhang, S. (2019), “A novel multi-stage hybrid model with enhanced multi-population niche genetic algorithm: an application in credit scoring”, *Expert Systems with Applications*, Vol. 121, pp. 221-232.

Zhang, L., Pentina, I. and Fan, Y. (2021a), “Who do you choose? Comparing perceptions of human vs Robo-advisor in the context of financial services”, *Journal of Services Marketing*, Vol. 35 No. 5, pp. 634-646.

Zhang, W., Yang, D. and Zhang, S. (2021b), “A new hybrid ensemble model with voting-based outlier detection and balanced sampling for credit scoring”, *Expert Systems with Applications*, Vol. 174, p. 114744.

Zhu, X., Li, J., Wu, D., Wang, H. and Liang, C. (2013), “Balancing accuracy, complexity and interpretability in consumer credit decision making: a C-TOPSIS classification approach”, *Knowledge-Based Systems*, Vol. 52, pp. 258-267.

Appendix

The Appendix is available online for this article.

About the authors

Janin Karoli Hentzen is a PhD student at the University of Adelaide Business School. Her research interests are technology engagement and consumer financial decision-making. Specifically, she seeks to investigate how technology affects consumers’ daily lives.

Prof. Dr. Arvid Hoffmann is a Professor in Marketing at the University of Adelaide Business School. His research interests are interdisciplinary and bridge the fields of marketing and finance. In particular, he seeks to better understand how individuals make complex financial decisions. Arvid Hoffmann is the corresponding author and can be contacted at: arvid.hoffmann@adelaide.edu.au

Dr. Rebecca Dolan is a Senior Lecturer in Marketing at the University of Adelaide Business School. Her research interests focus on understanding, facilitating and optimizing customer relationships, engagement and online communication strategies. She has a specific interest in the role of digital and social media in the modern marketing communications environment.

Erol Pala is a PhD student at Auckland University of Technology. His research interests focus on the role of digital technology in consumer behavior.