Expectations of bank automation: the influence of consumer cognitive schema

International Journal of Bank Marketing

Alessandro Carretta
Tor Vergata University of Rome, Rome, Italy
Doriana Cucinelli
University of Parma, Parma, Italy
Lucrezia Fattobene and Lucia Leonelli
Tor Vergata University of Rome, Rome, Italy, and
Paola Schwizer
University of Parma, Parma, Italy

Received 28 May 2023
Revised 28 December 2023
6 May 2024
Accepted 9 June 2024

Abstract

Purpose – This study aims to investigate the drivers of bank automation system performance expectancy compared to that of bank employees. The purpose is to shed light on the role played by consumers' cognitive schema on automation that is the perfect automation schema (PAS).

Design/methodology/approach – A survey was administered to about 500 Italian subjects to measure their PAS; financial knowledge, anxiety, and security; and sociodemographic and socioeconomic variables. Ordered probit regressions and an instrumental variable two-stage least squares regression are run.

Findings – The analyses reveal that cognitive schemas play a crucial role in consumer expectations in banking. Individuals with stronger PAS tend to have more positive expectations about bank automation performance compared to employee performance. Financial anxiety and knowledge positively affect bank automation performance expectancy while women, older people, and financially insecure subjects have poor expectations of automated banking systems.

Originality/value – This study extends the understanding of key consumer characteristics that affect bank automation performance expectancy compared to that of bank employees in services delivery in the Italian context. Moreover, it provides useful results for researchers, practitioners, banking institutions, and regulators.

Keywords Consumers, Human-computer service interactions, Individual traits, Cognitive schema, Financial services, Banking

Paper type Research paper

1. Introduction

After the 2008 Global Financial Crisis, the banking industry's focus shifted; instead of prioritizing innovation, the industry began to prefer product operations that generated the highest revenue (Northey *et al.*, 2022). However, with the onset of the COVID-19 pandemic in early 2020, the world experienced widespread social distancing, lockdowns, and isolation measures. These circumstances accelerated the process of digital transformation within the banking sector, reshaping payments, wealth management, lending, and insurance (Bank for

Funding: The study was funded by Beyond Borders 2019 - Tor Vergata University of Rome.

International Journal of Bank Marketing
Emerald Publishing Limited
0265-2323
DOI 10.1108/IJBM-05-2023-0309

International Settlements, 2021). Artificial intelligence and automation are significantly impacting both consumers and financial institutions (Mogaji *et al.*, 2021a, b; Molina-Collado *et al.*, 2021). Smart wallets, robo-advisors, and voice assistants (Donepudi, 2017), selfie-pay (Tomić and Todorović, 2018), blockchain (Kshetri and Voas, 2018), and self-driving cars with bank accounts (King, 2018) are just a few examples of how banks are exploiting automation in their daily operations. Most bank customers opt to oversee their banking affairs and handle their accounts via mobile applications or computer platforms (American Banking Association, 2023), while online transfers and electronic payments have become the prevailing methods of conducting transactions (Eurostat, 2023).

Although growth has recently emerged in research on artificial intelligence and automation in the banking industry and how it impacts consumer behavior (see Hentzen *et al.*, 2022 for a comprehensive literature review), existing studies have not fully explored consumer needs, attitudes, and preferences regarding the transition from human-led to AI-informed financial services delivery and its implications (Mogaji *et al.*, 2022). In the financial services industry, employees play a fundamental role in meeting consumer needs (Bahadur *et al.*, 2020; Wieseke *et al.*, 2012) and how consumers perceive employees compared to automation affects financial behavior (Raza *et al.*, 2023; Northey *et al.*, 2022; Lee and Wang, 2023; Chou *et al.*, 2023; Riedel *et al.*, 2022; Zhang *et al.*, 2021). However, research on the variables that affect consumer performance expectancy is scant (Wang *et al.*, 2017; Shaikh and Karjaluoto, 2015). In spite of the surge in banking and finance digital solutions, research to date has not yet determined the key investor-related characteristics that drive their adoption (Fan, 2022; Hentzen *et al.*, 2022). Furthermore, the determinants of successfully providing financial services through automation remain an open question (Zhang *et al.*, 2021). This study aims to fill this gap by investigating whether consumers vary in their cognitive schema toward automated systems—in other words, the perfect automation schema (PAS) (Merritt *et al.*, 2015)—and if this individual characteristic is related to automated system performance expectancy in the banking sector.

Based on a gender and education stratified sample of Italian adults, a set of ordered probit regressions is used in this study to examine whether and how consumer PAS is related to their bank automation performance expectancy compared to that of employees.

Previous findings highlight that country-level cultural context influences an individual's attitudes toward algorithms, and individualistic countries are less likely to follow algorithms (Duan *et al.*, 2019; Rau *et al.*, 2009). Moreover, the literature shows that the performance expectancy construct is especially relevant in countries with cultures of high individualism (Zhang *et al.*, 2018), and, according to Hofstede, Italy has a high individualism index. Finally, Italy lags behind other European countries in digital technology usage, as revealed by the Digital Economy and Society Index (2022) and shows a very low adoption rate in digital financial services (Dumicic *et al.*, 2015; Filotto *et al.*, 2021; Migliore *et al.*, 2022; Statista, 2023a, b). Therefore, we conducted a single-country study focused on Italy. Given the influence of individual factors in shaping interactions with automated systems and financial behavior (Lusardi and Mitchell, 2011; Grable *et al.*, 2014; Deloitte, 2019; Andreou and Anyfantaki, 2021; Mahmud *et al.*, 2022) we also explore the roles played by variables related to financial well-being, financial literacy, demographics, and socioeconomic status. We further perform some robustness analyses to check our results, including running an instrumental variable (IV) two-stage least squares (2SLS) regression.

Our findings show that consumer cognitive schema affect their tendency to believe that, compared to human bank employees, automated banking systems are more prone to error. Subjects who display stronger PAS are more likely to believe that automated banking systems are efficient and less error prone than bank employees. This result is not obvious, since the perception of automation in general contexts cannot be directly transposed into the banking domain given consumers' tendency to have different perceptions of automation applied to specific risky contexts, such as medical or military ones (Longoni *et al.*, 2019; Pearson *et al.*, 2019). Moreover, generalizing the findings from other decision domains is not possible because the literature shows the influence of high-level factors on automation adoption (Lourenço *et al.*, 2020; Mahmud *et al.*, 2022); consequently, the banking sector deserves specific investigation.

The results also confirm the relevance of financial knowledge, anxiety, and security for financial behavior. Findings show that performance expectancy in banking is related to other individual differences and that higher levels of financial anxiety and knowledge are associated with more positive bank automation performance expectancies compared to those of employees. Conversely, the more secure a subject feels with their current and future financial situation, the lower their performance expectancy of automated banking systems.

Our study's contribution to the literature is threefold. First, to the best of our knowledge, this is the first study to explore the influence of cognitive schema on consumer bank performance expectancy; thus, it contributes to the literature on individual differences and financial decision-making. The literature on automation and artificial intelligence tends to explore the effects of AI and automation on consumers' psychological consequences and behaviors (Cui, 2022; van Esch and Cui, 2021; van Esch and Stewart Black, 2021; van Esch *et al.*, 2021a, b). However, in this study, we step back to investigate what drives consumer performance expectancy of bank automation compared to that of employees; understanding such drivers is crucial in affecting intention to use and actual usage of digital solutions (Wang *et al.*, 2017; Gan *et al.*, 2021; Cheng-Xi Aw *et al.*, 2023; Rühr *et al.*, 2019; Nourallah, 2023). Second, previous studies have shown the importance of the industry in which automation is embedded in its effect on subject preferences and behavior (Dietvorst *et al.*, 2015; Berger *et al.*, 2021; Kawaguchi, 2021). Thus, we contribute to the literature that investigates the banking sector. This deserves special attention because it is a high-involvement service context characterized by high personal relevance and is therefore dominated by high-touch personal relationship service delivery (Vlaev *et al.*, 2009; Zhang *et al.*, 2021). Finally, we contribute to the literature on algorithmic decision-making by exploring the influence of individual, organizational, and cultural factors.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature and states the main research hypothesis, while Section 3 describes the methods, questionnaire, data collection, variable measures, and econometric models. Section 4 presents the empirical results, Section 5 discusses the key findings, and Section 6 draws some conclusions.

2. Literature review and hypothesis development

Our study relates to two different streams of research in the financial services industry: the literature on performance expectancy and that on comparisons between human employees and automation.

In recent decades, automation has strengthened banking services, benefiting many users (Mogaji *et al.*, 2021a, b). Nevertheless, marketing researchers emphasize that it is a challenge to understand the factors that drive its success (Sheth *et al.*, 2022). Although automation in banking is associated with many advantages for consumers, empirical investigations reveal that consumers still prefer human interactions and tend to perceive AI performance as inferior to that of employees (Zhang *et al.*, 2021). Consequently, consumer acceptance of automation is generally low (Hildebrand and Bergner, 2020; Wexler and Oberlander, 2021; Zhang *et al.*, 2021).

Over time, numerous theories have been proposed to pinpoint the factors that drive technology acceptance. One of these, the unified theory of acceptance and use of technology

(UTAUT), is considered the most comprehensive research model for predicting consumer behavior, including in banking (Alalwan *et al.*, 2017; Martins *et al.*, 2014), since it is able to explain about the 70% of the variance in behavioral intentions. This theory highlights the prominent role of performance expectancy as one of the primary determinants of technology adoption (Cheng-Xi Aw *et al.*, 2023). Performance expectancy is defined as the degree to which individuals believe automation can help improve the performance of jobs or other activities (Venkatesh *et al.*, 2003, 2012). It is considered the strongest predictor of behavioral intentions, which, in turn, have a significantly positive influence on technology usage (Venkatesh *et al.*, 2003, 2012). Performance expectancy also has a strong effect on intention to use and usage of automation in the banking and finance sector (Wang *et al.*, 2017; Shaikh and Karjaluoto, 2015). Conducting a weight and meta-analysis of 57 articles and 58 datasets, Baptista and Oliveira (2016) find that performance expectancy has a positive and statistically significant relationship with intention to use mobile banking services. This intention is directly and positively related to usage and has a direct positive and statistically significant relationship with mobile banking use itself. Akhlaq and Ahmed (2013) and Wang *et al.* (2017) report that performance expectancy significantly impacts acceptance of e-banking. Investigating the pandemic period, Gan *et al.* (2021) observe that performance expectancy drives consumer intention to subscribe to online financial robo-advisors. Focusing on a large consumer panel survey in China, Cheng-Xi Aw *et al.* (2023) observe that performance expectancy is crucial for robo-advisory service acceptance, while Rühr *et al.* (2019) find that performance expectancy has a significantly positive effect on intention to use an investment management system. Studying young retail investors in Malaysia and Sweden, Nourallah (2023) observes that trust in financial robo-advisors and behavioral intentions to use this technology are strictly related to performance expectancy.

Recent research on the UTAUT model has expanded to investigate how cultural values impact consumer intentions' adoption of digital financial services. Studies indicate that cultural values – measured using Hofstede's cultural dimensions - play a significant role in shaping the adoption rates of these services, providing insights into why they vary across countries (Blut *et al.*, 2022). Examining one of the key variables in the UTAUT model, such as performance expectancy, a cross-country comparison study found that individualism is a significant culture-related factor that enhances the effect of performance expectancy on the intention to adopt digital financial services (Migliore *et al.*, 2022). Italy, which ranks high in individualism (with a score of 76 compared to China's 20; Hofstede, 2001), also has a notably low adoption rate for digital financial services. Previous studies highlight a substantial adoption gap in mobile payment systems (Migliore *et al.*, 2022), indicating that Italy shows resistance to direct banking (Filotto *et al.*, 2021). Italy ranks among the lowest for digital financial service adoption among the 27 EU Member States (Dumicic *et al.*, 2015). Given these factors, examining the performance expectations of Italian consumers with regard to bank automation could yield valuable insights into the low adoption rates of digital financial services in the country.

The present study also relates to the stream of research in the financial services industry that focus on comparisons between human employees and automation. In the retail financial industry, consumers have relevant bargaining power since they can compare the financial products and services offered by financial intermediaries with those offered by competitors (Raza *et al.*, 2023). In this type of market, employee performance becomes highly relevant (Aburayya *et al.*, 2020; Liao and Chuang, 2004); thus, the financial services industry is one where employees play an essential role in meeting consumer needs (Bahadur *et al.*, 2020; Wieseke *et al.*, 2012). The literature on customer-bank relationships suggests that for enduring relationships—which are important for bank profitability—employee conduct is crucial since it affects both perceptions of service performance and the subsequent behavioral outcomes (Lachance and Tang, 2012; Wasan, 2018). In fact, in service encounters between customers and employees, the latter are usually considered primarily responsible for favorable or unfavorable performance (Swanson and Davis, 2003).

Few studies have focused on consumer perceptions of employees compared to perceptions of automation and how these perceptions influence financial behavior. Raza *et al.* (2023) explore how consumer perceptions of frontline employees' empathy and customer orientation affect their opinions regarding employee performance; they observe a significant role of the latter, with trust playing a mediating role. Northey *et al.* (2022) investigate whether and how investment intention in a retail banking context is affected by advisor type, comparing a human advisor to a robo-advisor; their experimental approach shows that the customer level of involvement, belief in the information conveyed, and perception of the bank's customer focus play crucial roles in investment decisions. Lee and Wang (2023) examine the influence of push, pull, and mooring factors on customer intentions to switch from traditional wealth management services to mobile wealth management applications. They detect the influences of perceived inconvenience, transaction efficiency, perceived personalization, mobile wealth management scenarios, affective commitment, and product market expertise. Chou *et al.* (2023) further explore the relationship between robo-advisors and traditional banking, highlighting that financial consultant and bank institution trust are antecedents of banks' intangible value binding in robo-advisor services. Also focusing on the financial advisory context, Riedel *et al.* (2022) study artificial intelligence vs human delivery of financial advice and report that political ideology, emotions, trust, and investment amount impact marketing outcomes such as consumer word-of-mouth and brand attitudes. In the same research stream, Zhang *et al.* (2021) focus on the perceptions of robo-advisors compared to those of human advisors with high/low expertise, in terms of trust, performance expectancy, and intention to use. They observe that consumers prefer human expert financial advisors with high expertise to robo-advisors and expect better performance from human advisors.

Table 1 presents an overview of the existing literature in this topic area and the related findings.

How humans interact with automation, robots, and machines has been investigated by interdisciplinary and cross-disciplinary research in fields such as social cognition, psychology, robotics, and neuroscience; the findings show that individual reactions to automation are not straightforward (Logg *et al.*, 2019; Longoni *et al.*, 2019; Cui, 2022). Some studies reveal that, when interacting with automation, individuals use different cognitive schemas (Madhavan and Wiegmann, 2007; Lyons and Guznov, 2018; Merritt *et al.*, 2015; Parasuraman and Riley, 1997; Lou *et al.*, 2022). According to the psychology literature, a schema is a framework of cognitive knowledge that subjects use to organize information when dealing with a specific concept, topic, or stimulus (Fiske and Linville, 1980) to interpret and make sense of the world around them (Fiske and Taylor, 1991). In their seminal work, Dzindolet *et al.* (2002) observe that when provided with human and automated aids, subjects tended to underutilize both types and prefer to rely on themselves. To explain their behavior when using the automated aid rather than the human one, subjects indicated specific errors they believed the aid had committed, thus showing the crucial role of performance expectancy. Schemas are widely applied to consumer behavior, and marketing research has found that they are particularly useful in studying consumer preferences (Sjödin and Törn, 2006; Fournier, 1998; Boush and Loken, 1991; Rossiter *et al.*, 1991; Lou *et al.*, 2022). Consumers' cognitive schemas significantly influence their expectations (Stayman *et al.*, 1992). Discrepancy theory suggests that these expectations, especially those related to performance, are closely tied to satisfaction (Wirtz and Mattila, 2001). A discrepancy arises when a consumer's actual experience does not align with their expectations. If reality falls short of expectations (negative discrepancy), it can result in unfavorable outcomes. On the other hand, a positive discrepancy—where reality exceeds expectations—often leads to favorable outcomes (Torres and Kline, 2013). By examining the relationship between

Table 1. Overview of the most relevant studies on consumer perceptions of human employees vs automation in the banking industry

Authors	Focus/aim	Setting	Methodology	Sample	Results	Variables	Theoretical contributions	How our study extends previous findings
Raza *et al.* (2023)	The relationship between frontline employee empathy/client orientation, consumer trust, and frontline employee performance	Pakistan	Survey	375	Customer perceptions of frontline employee consumer orientation is positively related to the extent they *perceived* them as *performant*	Mediator: trust	They underscore the importance of applying *social exchange theory*, which indicates that employees' strategic personal resources encourage reciprocal interactions, ultimately enhancing their performance perception	Our study delves into the variables that are related to performance perception, comparing automation to employees Our study suggests that in investigating the link between employees' personal resources and clients' perception of their performance is important to take into account the clients' cognitive schema
Northey *et al.* (2022)	Influence of the advisor type (human vs robo) on investment intentions	US	Experiments (between subjects)	Study 1: 165 Study 2: 299	When the level of involvement is high, consumers believe the financial advice provided by *a human over that of a robo-advisor*	Dependent variable (DV): intention to invest Independent variable (IV): advisor type and involvement Mediators: belief in the financial advice; firm's perceived customer orientation	Their research expands on the factors that lead to adoption by uncovering an inhibiting role of robo-advisors. They also identify the conditions under which this occurs and the underlying psychological processes that drive these effects	Our study investigates the antecedents of attitudes toward automation vs attitudes toward human employees in banking, extending studies that focus on advisor type. We also consider a different geographical setting. Finally, we expand the theory on the underlying psychological process which affect customers' performance expectancy
Riedel *et al.* (2022)	Influence of the advisor type (human vs AI) on marketing outcomes	US	Online experiment	Study 1: 174 Study 2: 440 Study 3: 187	AI is associated with lower levels of word of mouth (WOM) and brand attitude compared to *human advisors*	DV: WOM, brand attitudes Mediators: emotion, trust Moderators: political ideology	Following the *affect-as-information theory*, their research demonstrates that in AI-based financial services, emotional responses serve as a source of information that shapes the evaluation of the service, impacting trust and subsequently marketing outcomes	

(*continued*)

Authors	Focus/aim	Setting	Methodology	Sample	Results	Variables	Theoretical contributions	How our study extends previous findings
Lee and Wang (2023)	Users' intentions to switch from traditional wealth management services to mobile settings (apps)	China	Survey	378	*Switching intention* is affected by several push (i.e. *perceived inconvenience*), pull, or mooring factors	DV: switching intentions IV: perceived information asymmetry; perceived inconvenience; ubiquity; transaction; perceived personalization; mobile wealth management scenarios; affective commitment; wealth management product market expertise; switching costs (sunk costs and setup costs)	They apply the *push-pull-mooring framework* to explore the main factors that lead users to transition from traditional wealth management services to mobile wealth management apps	Our paper extends these findings on the evidence that perceived inconvenience affects individuals' behavioral willingness and consumer behavior focusing on an original antecedent of performance expectancy
Chou *et al.* (2023)	The importance of bank intangible value binding in customers' robo-advisory adoption and the influence of trust in the banking institution and the financial consultant	Taiwan	Survey	228	Intangible value bindings mediate the relationship between trust and consumer willingness to adopt robo-advisors. Consumers' investment amounts negatively impacts the positive relationship between intangible value binding and *robo-advisor adoption intention*	DV: robo-advisor adoption intentions IV: financial consultant trust, bank institution trust Mediator: intangible value binding Moderator: amount of customer investment in the bank per year	Their study presents a holistic approach, highlighting the value of bank intangible value bindings in driving customers' adoption of robo-advisors. They suggest a hybrid model that blends robo-advisors with traditional banking, promoting the acceptance of robo-advisors	Our study extends research on the driver of automation adoption by shedding light on an individual variable that affects automation performance expectancy compared to that of employees. Our study contributes to theory by examining how cognitive processes affect the factors leading to the acceptance of digital services
Zhang *et al.* (2021)	Individual differences in perceptions of trust, performance expectancy, and intention to hire human vs robo-advisors, with low/high levels of expertise	US	Online experiment	Study 1: 188 Study 2: 189 Study 3: 185	Consumers trust expert *humans* more, expect *better performance*, and express greater intention to hire them compared to a *robo-advisor*	DV: performance expectancy, trust IV: advisor type, expertise	Building on research related to the adoption of self-service technology (SST), this study analyzed perceptions of robo vs human advisors, focusing also on performance expectancy	Our study extends research on individual differences in perceived performance expectancy considering the perfect automation schema as a new variable. Our study offers a theoretical contribution by recommending that researchers consider customers' cognitive schemas when examining the adoption of SST

Source(s): Created by authors

Table 1.

performance expectations and actual experience, discrepancy theory provides a useful framework for understanding consumer behavior.

Given that individuals differ in their representations of automation performance expectancy and that these representations might be affected by different cognitive schemas (Lou *et al.*, 2022), PAS appears to be a useful construct for analyzing bank automation performance expectancy compared to that of employees. PAS consists of two complementary dimensions relating to subjects' expectations of automation performance and errors. The *high expectations* dimension captures the degree to which people expect automation to perform with near-perfect reliability. The *all-or-none* dimension captures the degree to which people expect automation to work perfectly or not at all (Merritt *et al.*, 2015). We posit that the general cognitive schema toward automation translates into bank automation performance expectancy compared to that of bank employees so that subjects with stronger PAS have more positive performance expectancy of automated banking systems than they do of bank employees. We thus formulate the following hypothesis:

H1. Consumer PAS is positively related to consumer bank automation performance expectancy.

3. Methods

3.1 The questionnaire

The questionnaire was organized into three sections. The first section included four items to collect certain sociodemographic and socioeconomic information from the subjects: gender, age, education, and income level. Previous research shows that these characteristics are related to financial behaviors and attitudes (Ambuehl *et al.*, 2014; Finke *et al.*, 2017) and algorithmic decision making (Mahmud *et al.*, 2022). Therefore, we include them as control variables in our model estimation to gain more nuanced estimates of the partial effects of PAS on subjects' bank automation performance expectancy compared to that of employees.

In the second part of the survey, the subjects' feelings toward automation systems were evaluated. PAS was assessed using the 7-item scale created by Merritt *et al.* (2015). Four items assessed *high expectations* (PAS1); an example item was: "Automated systems rarely make mistakes." Three items assessed *all-or-none thinking* (PAS2); an example item was, "If an automated system makes an error, then it is broken." All items were evaluated using a 5-point Likert-type scale ranging from strongly disagree to strongly agree. We measured the performance expectancy of bank automation compared to performance expectancy of employees (Bank_automation_perf) with three items developed by the authors. These items asked subjects to evaluate (using a scale ranging from one (strongly disagree) to five (strongly agree) the extent to which they believed that, compared to bank employees, bank automation systems: (1) are perfect, (2) rarely make mistakes, and (3) are preferable because they have lower error rates. Instead of measuring performance as the likelihood that automation will lead to a positive outcome, we relied on a multi-item measure for performance expectancy adapted from Zhang *et al.* (2021) that compares automation to human employees (Northey *et al.*, 2022; Riedel *et al.*, 2022). The higher the index, the more positive the performance expectancy of automated banking systems compared to that of employees. To ensure the equivalence of the translated Italian version of the PAS questionnaire and the original version, translation and back-translation were performed into their mother tongues by two independent translators.

The previous literature underlines the importance of considering financial well-being and knowledge when studying financial behavior (Grable *et al.*, 2014; Lusardi and Mitchell, 2011; Andreou and Anyfantaki, 2021; Deloitte, 2019). Therefore, in the survey's third section, we included the Financial Anxiety Scale (FAS) (four items) (Fünfgeld and Wang, 2009) and

Financial Security Scale (FSS) (three items) (Strömbäck *et al.*, 2017). The subjects were asked to indicate to what extent they agreed with the statements presented, with scale options ranging from 1 (not at all) to 5 (completely agree). An example item related to FAS is "I am anxious about my financial matters and those related to money in general," while an example item of the FSS scale is "I feel safe in my current financial situation." To obtain the final variables, we used the average score obtained from the four and three items, respectively. To measure financial knowledge (FK), we presented the so-called "big five" questions, that is, the Lusardi and Mitchel questions (Lusardi and Mitchell, 2011), which include questions about inflation, the time value of money, mortgage interest, risk diversification, and the relationship between interest rates and bond prices. We assigned 1 point for each question the respondent answered correctly and zero for each question answered incorrectly.

To obtain a general proxy for subjects' propensity to use automation solutions (the Internet), we asked how frequently they used the Internet in one month (including all use of the Internet, such as sending and receiving emails).

The variables used in the study and their definitions are presented in Table 2, while all questions are listed in the Appendix.

3.2 Sample

This study utilized a web-based online survey. The survey link was shared through a call posted on a major Italian university bulletin board; students were asked to share the

Symbol	Definition
bank_automation_perf	Subjects' performance expectancy of bank automation compared to that of employees—three items (range 1–5)
PAS 1 (high expectations)	Expectation that automated systems will perform with near-perfect reliability—four items from Merrit *et al.* (2015) (range 1–5)
PAS2 (all-or-none thinking)	Expectation that automation systems either work perfectly or not at all— three items from Merrit *et al.* (2015) (range 1–5)
PAS_total	Self-reported measures of perfect automation schema computed as the average of the sum of PAS1 and PAS2 (Merrit *et al.*, 2015)
strong_PAS	Strong tendency to have positive expectations of automated system performance measured as a dummy variable that equals 1 if respondent's PAS is at least equal to 3
FAS	The Financial Anxiety Scale measures subjects' anxiety related to money matters using four items from Fünfgeld and Wang (2009) (range 1–5)
FSS	The Financial Security Scale measures subjects' perceived security related to money matters using three items from Strömbäck *et al.* (2017) (range 1–5)
FK	The Financial Knowledge Score is the sum of the number of correct responses to the Big5 financial literacy questions (Lusardi and Mitchell, 2011) (range 1–5)
GEND	A dummy variable that equals 1 if the respondent is a woman, and zero otherwise
AGE	Age of respondent. We consider different age groups and include a dummy variables for each age group
EDU	Educational level, distinguishing among students up to primary, middle, high school, university degree, and PhD/post degree master
INC	Income level is the natural logarithm of family income reported by the respondent
Internet	A proxy for propensity to use automation systems based on how frequently respondents use the Internet in one month (never/once a month, a few times in a month, more than five times in a month). Three different dummy variables are included, one for each category

Source(s): Created by authors

Table 2. Variables and definitions

questionnaire with other adults. To determine the size required based on the desired power, we used *G*Power* software (Faul *et al.*, 2007, 2009), which showed that we would need at least 533 respondents to detect a medium effect at 95% power. Following Lee *et al.* (2020) we set the following parameters to calculate the appropriate sample size: effect size—0.25, alpha—0.05, and power—0.95. Over a period of one week, the survey was accessed 709 times. Responses that were incomplete were removed, leaving 572 valid and complete responses; based on the power analysis, this size is adequate for this study. Our demographic analysis indicates that 49.65% of our subjects are women ($n = 284$) and about half of the sample (58.39%, $n = 334$) are subjects between 19 and 25 years old. In terms of education and income, 67.13% ($n = 384$) of them have at least a college degree, and 68.49% ($n = 389$) have income lower than 10,000 euros. The sample is stratified in terms of gender and educational level, representative of the composition of the distribution of Italian adults. In term of age, the sample is slightly slanted toward younger individuals, due in part to the initial use of university students as subjects. We initially distributed our questionnaire among university students; only in a second step it was distributed to other adults. However, although mainly based on university students, our sample is in line with other studies that investigate customer behaviors by collecting information from students (see, e.g. Bongini and Cucinelli, 2019; Aydin and Akben Selcuk, 2019). Table 3 reports the sample composition.

3.3 Regression analyses

Since our dependent variable can assume values ranging from 1 to 5, to detect the determinants of subjects' banking automation system performance expectations, we run an ordered probit regression as shown in Eq. (1) (Model 1):

Variables	*N*	%
Gender	288	50.35
Male	284	49.65
Female		
Age	334	58.39
19–25	41	7.17
26–35	13	2.27
36–45	79	13.81
46–55	77	13.29
56–65	8	1.4
>65		
Education	152	26.22
University or postgraduate	384	67.13
High school	36	6.29
Less than high school		
Income (euros)	389	68.49
Less than 10K	106	18.66
10–24K	51	8.63
25–39K	26	4.23
More than 40K	572	100
Total		

Note(s): Table 3 reports the sample descriptive statistics with the number of observations and percentage of each category

Source(s): Created by authors

Table 3.
Sample description

$$Y_i = \alpha + \beta_1 PAS_i + \beta_2 FAS_i + \beta_3 FSS_i + \beta_4 FK_i + \beta_5 FK_i + \beta_6 GEND_i + \beta_7 AGE + \beta_8 EDU + \beta_9 INC + \varepsilon \quad (1)$$

where Y is the dependent variable *bank_automation_perf* measured for each individual i. As independent variables, we include all variables described in Section 3.1: PAS, FAS, FSS, FK, and the sociodemographic and socioeconomic characteristics. Research highlights that the probability that a person engages the service of a human financial adviser decreases when the level of financial anxiety is high (Grable *et al.*, 2014), thus a positive relationship between financial anxiety (FAS) and *bank_automation_perf* can be expected. Industry report reveal that subjects with high financial security tend prefer human relationship (Deloitte, 2019), thus we expect a negative relationship between FSS and *bank_automation_perf*. Since literature suggests that low levels of financial literacy could be holding consumers back from the embracement of digital channels (Andreou and Anyfantaki, 2021), we expect a positive relationship between FK and bank automation performance expectancy. AGE, EDU, and INC refer to a vector composed of several dummy variables, one for each category identified. ε is the error term.

As specified in Section 3.1 and Table 2, following Merritt *et al.* (2015), we distinguish the two components of PAS—*high expectation* (PAS1) and *all-or-non thinking* (PAS2)—and include them in the same regression model (Model 2). In a third regression model, to detect the relationship between a high PAS score and subjects' bank automation system performance expectancy, we include strong_PAS as an independent variable (Model 3). Thus, PAS alternatively assumes the values of PAS_total when we consider the average of PAS1 and PAS2; PAS1 or PAS2, when we include both PAS components in the regression; and strong_PAS when we insert a dummy that equals 1 if respondents had an average PAS_total higher than 3.

4. Results

4.1 Summary statistics

Table 4 reports the descriptive statistics of all variables included in the empirical model. On average, individuals show positive performance expectancy of automated banking systems ($M = 3.138$, SD = 0.727) and high expectations of automated systems in general. The PAS2 variable, on average, equals 2.698 (SD = 0.609) out of a total of 5; that is, higher than the average (2.5) but lower than the PAS1 score. Individuals show a high level of anxiety about money matters (M = 3.021, SD = 0.633) but also demonstrate high perceived security in their current and future financial situations ($M = 3.067$, SD = 0.696). The subjects' financial knowledge is not very high (M = 2.469, SD = 1.577); this is consistent with country results that highlight Italians' low level of financial knowledge (see, e.g. di Salvatore *et al.,* 2018). Cronbach's alphas are reported in the first column of Table 5. In all cases, the alphas are above or very close to 0.7, revealing that the constructs have good internal consistency (Hair *et al.*, 2014; Zeinalizadeh *et al.*, 2015; Vieira *et al.*, 2021).

Table 5 reports the correlations among the independent and control variables included in the empirical analysis; these correlations have low values. Interestingly, in line with the previous literature (Merritt *et al.*, 2015), the correlation between the variables PAS1 and PAS2 is low (r = 0.23), suggesting that while it is possible that high expectations and all-or-none thinking operate in conjunction, they also represent distinct constructs.

Table 6 presents the Variance Inflation Factors (VIF). VIF results indicate the absence of multicollinearity problems between the independent variables, with values well below 10 (Thompson *et al.*, 2017) and the mean ranging from 3.21 to 3.33.

Variables	M	Median	SD	Min	Max
bank_automation_perf	3.138	3.000	0.727	1.000	5.000
PAS1	3.049	3.000	0.680	1.000	5.000
PAS2	2.698	2.667	0.609	1.000	5.000
PAS_total	2.873	2.875	0.505	1.000	5.000
FK	2.469	3.000	1.577	0.000	5.000
FAS	3.021	3.000	0.663	1.250	5.000
FSS	3.067	3.000	0.696	1.000	5.000
GEND: female	0.497	0.000	0.500	0.000	1.000
AGE__19–25	0.584	1.000	0.493	0.000	1.000
AGE__26–35	0.072	0.000	0.258	0.000	1.000
AGE__36–45	0.023	0.000	0.149	0.000	1.000
AGE__46–55	0.138	0.000	0.345	0.000	1.000
AGE__56–65	0.133	0.000	0.340	0.000	1.000
EDU: univ	0.262	0.000	0.440	0.000	1.000
EDU: high sch	0.671	1.000	0.470	0.000	1.000
INC: <10K	0.685	1.000	0.465	0.000	1.000
INC: 10–24K	0.187	0.000	0.390	0.000	1.000
INC: 25–39K	0.086	0.000	0.281	0.000	1.000

Note(s): Table 4 reports the descriptive statistics of the variables included in the empirical models. The Table shows the average score, median value, standard deviation, minimum, and maximum for each variable
Source(s): Created by authors

Table 4.
Descriptive statistics

4.2 Regression results

Table 7 shows the results from the ordered probit regression conducted to ascertain the effects of PAS and individual characteristics on the likelihood that subjects have positive performance expectancies of bank automation.

Model 1, where the independent variable is PAS_total, computed as the average value of the sum of PAS1 and PAS2, is statistically significant ($W\,(15, N = 559) = 221.73, p < 0.001$). The results reveal a positive and statistically significant relationship with bank_automation_perf ($p < 0.001$), confirming our main hypothesis. Moreover, the variable FK has a statistically significant influence on bank_automation_perf ($p = 0.003$). With respect to sociodemographic and socioeconomic characteristics, the results reveal positive and statistically significant impacts on bank_automation_perf of AGE_19–25 ($p < 0.001$) and AGE_26–35 ($p = 0.048$), and the negative influence of EDU_Univ ($p = 0.043$).

Model 2, where PAS1 and PAS2 are included separately, is statistically significant ($W\,(16, N = 559) = 297.29, p < 0.001$), and the results reveal a significantly positive relationship between bank_automation_perf and PAS1 ($p < 0.001$). The relationship between bank_automation_perf and PAS2 is not statistically significant. The results show that AGE_19–25 has a statistically significant influence on bank_automation_perf ($p < 0.001$), while EDU_Univ ($p = 0.032$) has a negative one.

Model 3, where the independent variable is strong_PAS, is also statistically significant ($W\,(15, N = 559) = 132.2, p < 0.001$); the results reveal a positive and statistically significant relationship with bank_automation_perf ($p < 0.001$). The analysis detects that the variable FSS has a statistically significant influence on bank_automation_perf ($p = 0.047$). With respect to sociodemographic and socioeconomic characteristics, only AGE_19–25 has a positive and statistically significant impact on bank_automation_perf ($p = 0.013$).

4.3 Robustness check

PAS, our main variable of interest, for which we aim to detect a relationship with consumer expectations of automated banking systems, may depend on certain other variables that are

Table 5. Correlation matrix

		Cronbach's alpha	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	PAS_total	0.727	1.00																	
2	PAS1	0.841	0.81*	1.00																
3	PAS2	0.697	0.76*	0.23*	1.00															
4	FAS	0.699	0.05	−0.04	0.13*	1.00														
5	FSS	0.723	−0.18*	−0.14*	−0.13*	0.28*	1.00													
6	FK		0.01	0.10*	−0.09*	−0.13*	0.03	1.00												
7	GEND: female		−0.11*	−0.10*	−0.07	0.14*	0.12*	−0.20*	1.00											
8	AGE__ 19–25		−0.16*	−0.02	−0.24*	0.03	0.13*	−0.13*	−0.02	1.00										
9	AGE__ 26–35		−0.01	−0.02	0.01	−0.06	0.01	−0.04	0.01	−0.34*	1.00									
10	AGE__ 36–45		−0.01	0.03	−0.06	−0.05	−0.04	0.08	0.05	−0.18*	−0.04	1.00								
11	AGE__ 46–55		0.11*	0.03	0.14*	−0.04	−0.01	−0.01	0.08	−0.47*	−0.11*	−0.06	1.00							
12	AGE__ 56–65		0.15*	0.04	0.20*	0.03	−0.11*	0.21*	−0.06	−0.47*	−0.11*	−0.06	−0.16*	1.00						
13	EDU: univ		−0.03	−0.05	0.00	−0.03	−0.03	0.03	0.09*	−0.14*	0.28*	0.11*	−0.06	0.06	1.00					
14	EDU: high Sch		0.03	0.08*	−0.04	0.00	0.05	0.01	−0.07	0.29*	−0.26*	−0.11*	−0.01	−0.07	−0.86	1.00				
15	INC: <10K		−0.12*	−0.05	−0.14*	0.06	0.15*	−0.15*	0.06	0.50*	−0.08	−0.09*	−0.25*	−0.39*	−0.16	0.16*	1.00			
16	INC: 10–24K		0.07	0.02	0.09*	0.00	−0.03	0.07	0.02	−0.27*	0.10*	0.03	0.20*	0.11*	0.05	−0.08*	−0.71*	1.00		
17	INC: 25–39K		0.04	0.03	0.03	−0.07	−0.11*	0.08	−0.04	−0.32*	−0.01	0.13*	0.12*	0.30*	0.14	−0.10*	−0.45*	−0.14*	1.00	

Note(s): $*p < 0.05$
Source(s): Created by authors

Table 6. Variance inflation factors (VIF)

Variable	Model 1 VIF	Model 1 1/VIF	Model 2 VIF	Model 2 1/VIF	Model 3 VIF	Model 3 1/VIF
AGE__19–25	7.32	0.137	7.36	0.136	7.27	0.138
INC: <10K	6.62	0.151	6.63	0.151	6.74	0.148
EDU: univ	5.15	0.194	5.15	0.194	5.05	0.198
EDU: high sch	5.12	0.195	5.12	0.195	5.03	0.199
INC: 10–24K	4.79	0.209	4.8	0.208	4.89	0.204
AGE__56–65	4.07	0.246	4.08	0.245	4.01	0.250
AGE__46–55	3.87	0.258	3.87	0.258	3.86	0.259
AGE__26–35	2.88	0.347	2.88	0.347	2.9	0.345
INC: 25–39K	2.85	0.351	2.85	0.351	2.84	0.352
AGE__36–45	1.56	0.640	1.57	0.637	1.61	0.622
FSS	1.2	0.835	1.2	0.835	1.18	0.850
FAS	1.16	0.861	1.18	0.851	1.16	0.864
FK	1.14	0.877	1.17	0.851	1.16	0.863
GEND: female	1.12	0.889	1.13	0.888	1.12	0.897
PAS_total	1.1	0.906				
PAS1			1.11	0.898		
PAS2			1.23	0.815		
PAS_strong					1.05	0.949
Mean VIF	3.33		3.21		3.32	

Source(s): Created by authors

included in our analyses. This may lead to an endogeneity problem. Therefore, to control for this possible issue, we run additional robustness checks; in particular, we use an IV 2SLS regression where the IV is the respondent's frequency of internet access (Model 4, Table 8). The idea is that if individuals usually use the internet frequently, they may be more likely to use system automation and have positive expectations. Thus, PAS_total has been instrumented using the number of times that respondents declare to have accessed the internet per month as the IV. The results of the second stage of the IV regression (W (15, N = 559) = 62.37, p < 0.001) confirm our main findings; PAS positively affects individual performance expectancy of automated banking systems.

As further robustness checks, we run different OLS regressions; their results confirm the findings of the previous econometric models (Table 9). In Model 5 (F(15, 543) = 21.79, p < 0.001, R^2 = 0.34), PAS_total significantly predicted bank_automation_perf, β = 0.77, t(543) = 15.04, p < 0.001. In Model 6 (F(16, 542) = 31.81, p < 0.001, R^2 = 0.43), PAS1 significantly predicted bank_automation_perf, β = 0.64, t(542) = 18.23, p < 0.001, but PAS2 did not, in line with Model 2. In Model 7 (F(15, 550) = 11.25, p < 0.001, R^2 = 0.22), strong_PAS significantly predicted bank_automation_perf, β = 0.57, t(550) = 1.10, p < 0.001. The control variables are the same across all four models. The robustness tests confirm that the impact of the control variables on our dependent variable is the same as that found in the main models.

5. Discussion

This study's main objective was to observe the drivers of consumer bank automation performance expectancy compared to their performance expectancy of bank employees in the Italian context. In the study, we considered for the first time, as an individual characteristic, the general cognitive schema of automated systems (PAS), besides the role played by financial security, anxiety, and knowledge. The relationship between PAS and bank automation performance expectancy is not straightforward; as demonstrated by previous studies, high-level factors, such as the organization that exploits the automation and decision

Table 7. Results of ordered probit regression: dependent variable is performance expectancy of bank automation compared to that of employees

	Model 1		95% CI			Model 2		95% CI			Model 3		95% CI		
	β	SE	LL	UL	p	β	SE	LL	UL	p	β	SE	LL	UL	p
PAS_total	*1.328*	0.102	1.128	1.529	0.000***	–	–	–	–	–	–	–	–	–	–
PAS1	–	–	–	–	–	*1.188*	0.079	1.034	1.342	0.000***	–	–	–	–	–
PAS2	–	–	–	–	–	0.111	0.081	−0.048	0.269	0.171	–	–	–	–	–
strong_PAS	–	–	–	–	–	–	–	–	–	–	*0.887*	0.098	0.696	1.079	0.000***
FK	*0.088*	0.029	0.031	0.145	0.003**	*0.043*	0.010	−0.057	0.142	0.089†	*0.049*	0.011	−0.046	0.143	0.090†
FAS	*0.235*	0.141	−0.041	0.511	0.095†	*0.403*	0.139	0.132	0.675	0.004**	*0.290*	0.136	0.024	0.555	0.033*
FSS	*−0.252*	0.135	−0.516	0.013	0.062†	*−0.227*	0.133	−0.487	0.033	0.087†	*−0.266*	0.134	−0.529	−0.003	0.047*
GEND: female	−0.115	0.089	−0.289	0.059	0.196	*−0.150*	0.088	−0.323	0.023	0.090†	*−0.173*	0.089	−0.347	0.001	0.051†
AGE_19–25	*0.897*	0.262	0.384	1.410	0.001***	*0.795*	0.248	0.309	1.282	0.001***	*0.605*	0.243	0.129	1.081	0.013*
AGE _26–35	*0.607*	0.307	0.006	1.207	0.048*	*0.564*	0.298	−0.021	1.149	0.059†	*0.547*	0.292	−0.026	1.119	0.061†
AGE _36–45	*0.809*	0.426	−0.026	1.644	0.058†	0.621	0.429	−0.220	1.462	0.148	0.292	0.466	−0.621	1.205	0.530
AGE _46–55	0.353	0.268	−0.173	0.879	0.188	0.398	0.250	−0.092	0.889	0.112	0.310	0.267	−0.212	0.833	0.245
AGE _56–65	0.369	0.289	−0.197	0.934	0.202	*0.501*	0.273	−0.034	1.036	0.067†	0.373	0.290	−0.195	0.942	0.198
EDU: univ	*−0.519*	0.257	−1.022	−0.016	0.043*	*−0.557*	0.260	−1.067	−0.048	0.032*	*−0.432*	0.241	−0.905	0.041	0.074†
EDU: high sch	−0.326	0.242	−0.800	0.148	0.178	*−0.405*	0.244	−0.883	0.073	0.097†	−0.190	0.227	−0.635	0.255	0.403
INC: <10K	−0.408	0.270	−0.937	0.121	0.130	−0.403	0.258	−0.909	0.103	0.118	−0.389	0.253	−0.884	0.107	0.124
INC: 10–24K	−0.286	0.282	−0.839	0.266	0.309	−0.269	0.269	−0.797	0.258	0.316	−0.271	0.265	−0.789	0.248	0.306
INC: 25–39K	−0.099	0.295	−0.678	0.480	0.738	−0.164	0.286	−0.723	0.396	0.566	−0.260	0.280	−0.808	0.289	0.354

Note(s): The Table reports the results of the ordered probit regression that has subjects' expectations of bank automated system performance as the dependent variable. PAS_total is the average value of PAS1 plus PAS2, which represents the perfect automation schema. PAS1 measures expectations of automated systems; PAS2 is a measure of "all-or-non thinking"; strong_PAS is a dummy variable that equals 1 if respondent has a PAS_total score that at least equals 3. β = beta coefficient; CI = confidence interval; LL = lower limit; UL = upper limit; p = p-value; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$<p < 0.1$
Source(s): Created by authors

Table 8.
Instrumental variable two-stage least squares regression where the IV is the respondent's frequency of internet access

Model 4	β	SE	95% CI LL	95% CI UL	p
PAS_total	*1.502*	0.566	0.391	2.612	0.008**
FK	*0.060*	0.020	0.021	0.099	0.002**
FAS	−0.040	0.070	−0.177	0.097	0.564
FSS	0.030	0.092	−0.151	0.211	0.745
GEND: female	0.022	0.090	−0.155	0.198	0.810
AGE_19–25	*0.529*	0.198	0.140	0.918	0.008**
AGE _26–35	0.278	0.206	−0.126	0.682	0.178
AGE _36–45	0.368	0.311	−0.241	0.978	0.236
AGE _46–55	0.048	0.218	−0.380	0.476	0.826
AGE _56–65	0.012	0.224	−0.427	0.452	0.957
EDU: univ	*−0.391*	0.186	−0.755	−0.027	0.035*
EDU: high sch	−0.305	0.190	−0.678	0.068	0.109
INC: <10K	−0.232	0.183	−0.591	0.127	0.206
INC: 10–24K	−0.167	0.187	−0.533	0.199	0.372
INC: 25–39K	0.012	0.204	−0.387	0.411	0.953
_cons	−1.156	−0.670	−4.522	2.210	0.501

Note(s): The table reports the results of the instrumental variable two-stage least squares regression where the dependent variable is the subjects' frequency of internet access. PAS_total is the average value of PAS1 plus PAS2, which represents the perfect automation schema. β = beta coefficient; CI = confidence interval; LL = lower limit; UL = upper limit; p = p-value; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
Source(s): Created by authors

domain largely affect this relationship (Longoni *et al.*, 2019; Pearson *et al.*, 2019). We posited that the general positive tendency toward automation applies to the banking sector, translating in a tendency to have positive performance expectancy of bank automation compared to that of bank employees.

The analysis revealed that PAS affects consumer tendency to believe that automated banking systems are prone to errors. Consequently, consumers that display strong PAS, as revealed by the variables PAS_total and strong_PAS, were more likely to believe that automated banking systems are efficient and less likely to commit errors than bank employees. The results show that the *high expectations* component of PAS is associated with a more positive view of bank automation performance expectancy compared to employee performance expectancy. The determinants of successfully providing financial services through automation are still not fully explored; this finding thus contributes to the literature on performance expectancy and the comparison between human employees and automation highlighting that in the Italian context consumer cognitive schemas are a crucial key consumer-related characteristic that drive performance expectancy in the banking sector.

Since expectations regarding bank error rates could be related to individual characteristics other than general PAS, we controlled for the potential role played by financial anxiety, security, and knowledge. In particular, we observed that higher consumer financial anxiety was associated with more positive expectations of automated banking systems. Previous studies suggest that insecurity can be alleviated by a clear decision-making process (Fünfgeld and Wang, 2009). Therefore, by eliminating conversation, interactions, reasoning, and discussions, automated banking systems can be perceived as an aid to making clear financial decisions, increasing the comfort of this category of subjects. In this sense, the literature on nudge theory (Thaler, 1994) suggests that automated measures can be one way to improve financial decisions. For instance, with respect to retirement plans, automated regular annual payments in the three-pillar system allows these individuals to reduce their financial anxiety and improve their long-term financial decisions. Finally, one of

Table 9. Robustness tests. OLS regressions: dependent variable is performance expectancy of bank automated systems

	Model 5					Model 6					Model 7				
			95% CI					95% CI					95% CI		
	B	SE	LL	UL	*p*	B	SE	LL	UL	*p*	B	SE	*LL*	*UL*	*p*
PAS_total	*0.771*	0.051	0.670	0.872	0.000***	–	–	–	–	–	–	–	–	–	–
PAS1	–	–	–	–	–	*0.639*	0.035	0.570	0.708	0.000***	–	–	–	–	–
PAS2	–	–	–	–	–	0.059	0.044	−0.027	0.144	0.177	–	–	–	–	–
strong_PAS	–	–	–	–	–	–	–	–	–	–	*0.572*	0.057	0.461	0.683	0.000***
FK	*0.053*	0.017	0.020	0.086	0.002**	*0.027*	0.016	−0.005	0.059	0.095†	*0.026*	0.008	−0.010	0.062	0.090†
FAS	0.027	0.044	−0.059	0.113	0.535	0.067	0.011	−0.014	0.148	0.090	*0.061*	0.049	−0.035	0.157	0.210*
FSS	*−0.129*	0.066	−0.260	0.002	0.053†	*−0.065*	0.038	−0.139	0.008	0.082†	−0.115	0.047	−0.208	−0.023	0.014
GEND: female	−0.061	0.052	−0.163	0.040	0.237	*−0.076*	0.018	−0.169	0.017	0.090†	*−0.105*	0.056	−0.216	0.005	0.062†
AGE_19–25	*0.512*	0.154	0.210	0.814	0.001***	*0.415*	0.133	0.154	0.677	0.002***	*0.382*	0.159	0.070	0.694	0.016*
AGE _26–35	*0.328*	0.180	−0.026	0.682	0.069†	*0.278*	0.160	−0.037	0.592	0.084†	*0.328*	0.190	−0.045	0.702	0.085†
AGE _36–45	*0.450*	0.254	−0.048	0.949	0.077†	0.314	0.236	−0.149	0.776	0.184	0.173	0.297	−0.411	0.757	0.561
AGE _46–55	0.199	0.160	−0.115	0.512	0.214	0.204	0.136	−0.062	0.471	0.132	0.192	0.175	−0.152	0.535	0.273
AGE _56–65	0.199	0.169	−0.132	0.531	0.237	*0.253*	0.146	−0.034	0.540	0.084*	0.227	0.187	−0.140	0.595	0.224
EDU: univ	*−0.309*	0.145	−0.594	−0.025	0.033*	*−0.310*	0.136	−0.577	−0.042	0.023*	*−0.282*	0.151	−0.579	0.015	0.063†
EDU: high sch	−0.190	0.137	−0.459	0.078	0.165	*−0.220*	0.128	−0.471	0.030	0.085†	−0.119	0.142	−0.399	0.160	0.402
INC: <10K	−0.224	0.154	−0.527	0.078	0.146	−0.204	0.138	−0.476	0.067	0.140	−0.237	0.159	−0.549	0.075	0.136
INC: 10–24K	−0.155	0.162	−0.472	0.162	0.338	−0.131	0.144	−0.414	0.152	0.364	−0.162	0.167	−0.490	0.166	0.332
INC: 25–39K	−0.046	0.169	−0.379	0.286	0.784	−0.077	0.153	−0.378	0.224	0.615	−0.157	0.176	−0.503	0.188	0.372
_cons	0.947	2.880	0.302	1.593	0.004	1.071	0.290	0.503	1.640	0.000	3.063	0.324	2.426	3.699	0.000

Note(s): The Table reports the results of the ordered probit regression where the dependent variable is subjects' expectations of automated banking systems performance. PAS_total is the average value of PAS1 plus PAS2, which represents the perfect automation schema. PAS1 measures expectations of automated systems; PAS2 is a measure of "all-or-non thinking"; strong_PAS is a dummy variable that equals 1 if the respondent has a PAS_total score that equals at least 3. B = non standardized beta coefficient; CI = confidence interval; LL = lower limit; UL = upper limit; p = p-value; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †< $p < 0.1$

Source(s): Created by authors

the items that measures this consumer trait is related to a negative feeling associated with the lingo used by financial experts; thus, it is not surprising that subjects who score high in this trait tend to have positive expectations of automated banking systems, likely preferring digital interactions to human ones.

We also observed that the less secure a subject feels about their current and future financial situation, the higher their expectations about automated banking system performance. A possible explanation is that subjects who believe their financial situation is insecure are likely to be more vigilant about their resources. They tend to be up-to-date on the different tools available to manage their money; thus, they recognize the potential offered by automation and artificial intelligence. Another possible interpretation of this finding is related to the subjects' financial experience. If they perceive that they can easily meet all their current commitments and have the financial resilience to maintain that situation in the future, they might be likely to attribute this positive status to the interactions they have had so far with their banking institution's employees and their financial advisor. In fact, the widespread use of digital solutions in banking services is a recent phenomenon, making it highly probable that consumers have had more fruitful interactions with employees than with algorithms, making them more averse to digital interfaces.

With the increasing complexity of available financial products and services, consumers are also offered a wide array of tools for accessing them and better managing their financial resources. Automation in banking allows consumers to easily manage their personal finances, including savings, payments, borrowing, investing, and risk management (Lyons and Kass-Hanna, 2021). Congruently, our findings reveal that subjects with greater financial knowledge might be more prone to take advantage of the opportunities offered by banking automation and thus have positive expectations about its performance.

The literature review shows that the degree of automation acceptance varies depending on sociodemographic and socioeconomic characteristics (Mahmud *et al.*, 2022). Our findings underline that female consumers are less likely to accept banking automation than men, in line with the results obtained in the different domains of health, justice, and media, where women have been found to perceive algorithms as less useful (Araujo *et al.*, 2020). Our study is also consistent with the previous literature that suggests younger consumers are more likely to adopt technology and automation (Flavián *et al.*, 2022). Although some studies report that higher educational levels are associated with greater appreciation of automation (Thurman *et al.*, 2019; Logg *et al.*, 2019), numerous studies reveal that professionals display the opposite tendency (Kaufmann, 2021). Our findings are consistent with this second cluster of studies, since we observe that individuals with higher education are less likely to have positive expectations of automated banking systems.

5.1 Theoretical contributions

This study offers different theoretical contributions. On one hand, previous studies have extensively investigated the importance for the UTAUT model of performance expectancy in the banking and finance sector, revealing that it is the primary determinant of technology adoption (Cheng-Xi Aw *et al.*, 2023; Wang *et al.*, 2017; Shaikh and Karjaluoto, 2015). On the other hand, another stream of research highlights the importance of employee performance in the banking and finance industry (Aburayya *et al.*, 2020; Liao and Chuang, 2004), investigating the factors that affect perceptions of employees compared to those of automation and their influence on financial behavior (Northey *et al.*, 2022; Lee and Wang, 2022; Chou *et al.*, 2023; Riedel *et al.*, 2022; Zhang *et al.*, 2021). This study contributes to these two streams of research by investigating the influence of cognitive schema. Recently, UTAUT research has expanded to consider the relevance of the cultural dimension in affecting performance expectancy and technology adoption, revealing the importance of the cultural individualism dimensions (Blut *et al.*, 2022; Migliore *et al.*, 2022). Our study concentrates on Italy, a country known for its high levels of individualism but comparatively low adoption rates of digital financial services (Dumicic *et al.*, 2015; Filotto *et al.*, 2021; Migliore *et al.*, 2022). The paper contributes shedding new light on the drivers of customer expectations regarding bank automation performance compared to those of bank employees, clarifying the role played by PAS. This result is interesting, because we empirically observe that individuals with high automation performance expectancy in general, who believe that automated services offer better outcomes than human employees, also display higher bank automation performance expectancy, likely considering automated financial services as more efficient than bank employees' services. In doing so, this study begins to address calls for exploring AI vs human employee service delivery, especially in financial services (Mogaji *et al.*, 2022).

Moreover, this study reinforces previous findings on the relationship between emotions and behavior in the financial domain, focusing in particular on financial feelings. Prior literature has examined emotional responses to AI (Castillo *et al.*, 2021; Riedel *et al.*, 2022; Cui, 2022); this study contributes confirming the relevance of the financial feelings in the financial decisions domain. Besides its utility in terms of accuracy and efficiency, the development of automation is defying a complex picture, which reveals intricate psychological consequences with downstream effects on consumers (van Esch and Cui, 2021; van Esch *et al.*, 2021a, b). Our findings confirm that financial security and anxiety affect bank customers' decision making. Our results are congruent with reports from industry (Deloitte, 2019) showing that high net worth individuals (i.e. those with high financial security) prefer human relationships, probably because they have lower expectations of bank automation performance (Northey *et al.*, 2022). At the same time, individuals with higher financial anxiety tend to prefer automated banking systems to reduce the probability of human errors. The results therefore add to the growing body of research across different service contexts that identify preferences for human interactions over automated systems.

5.2 Practical implications

Our findings also have relevant practical implications for banks, marketers, and policymakers. In countries like Italy, where the culture leans toward individualism, the idea of performance expectancy becomes crucial to understanding why people choose to adopt technology. Industry reports highlight that only 48% of people in Italy use online banking, compared to 98% in the United Kingdom (Statista, 2023a). Similarly, just 21% of smartphone users in Italy make use of proximity mobile payments, a stark contrast to the 81% in China (Statista, 2023b). These figures point to Italy's low adoption rates for digital financial services, making it intriguing to explore what influences consumers' expectations of automated banking services. Our research indicates that a person's general view of automation significantly impacts their expectations for digital banking services. The Italian data suggest that improving people's overall perception of automation and digital infrastructure could lead to higher adoption of digital financial services. Financial literacy has been identified as a key factor in encouraging positive financial behaviors (Lusardi and Mitchell, 2011; Andreou and Anyfantaki, 2021), and our findings suggest that increasing digital financial services adoption might be achieved by altering the public's mindset about the effectiveness of digital solutions. A practical approach to this could be enhancing digital literacy and skills.

Different individual expectations suggest that consumer attitudes and decisions in the financial context can be modulated by the means through which the service is provided, that is, whether by employees or an automated interface. In consumers with high PAS, risk perception can be enhanced when financial services are provided through automated systems rather than bank employees or financial advisors. Therefore, in the Italian context, financial industry practitioners might benefit from knowing that consumers differ in how they expect automation to perform, thus reducing technological interactions for those consumers with high PAS or, conversely, enhancing it for consumers who display the opposite trait.

This research sheds light on a new focal point for bank marketing strategies that has been largely disregarded by both theory and practice, that is, the cognitive schema consumers activate when interacting with automation. Traditionally, marketers have focused on gender, age, and education as the heart of their segmentation strategies. However, these variables do not enable businesses to identify all sub-market characteristics or improve their understanding of their target audience because consumers in the same demographic group may have heterogeneous psychographic makeups (Kotler and Armstrong, 2007). This study suggests that in the Italian context, consumers' cognitive schema should be considered when evaluating their performance expectations, which are strictly related to consumer intentions and behaviors. Collecting psychographic data is challenging; however, banks might exploit their close relationships with customers by administering short surveys to acquire information about their propensity toward automation and digital solutions. Banks that detect low PAS in their customers may want to consider a hybrid approach, mixing automated systems with human support, instead of completely replacing customer human interactions with automation.

Finally, from a consumer protection perspective, it is relevant to know that subjects differ in how they perceive automation in banking, and that this trait is likely to alter preferences and decisions. That is, financial consumers might avoid buying insurance, savings, or investment products depending on a manipulated factor as the means of interaction (i.e. a chatbot rather than a financial advisor). Overall, these practical implications point out the need to theoretically study and empirically investigate how subjects' cognitive schema toward automation influence their financial decisions.

5.3 Limitations and further development

This study has limitations that offer opportunities for further exploration. Firstly, although performance expectancy is a crucial variable in the UTAUT model, other factors also play a role, suggesting that future research could investigate whether cognitive schemas influence other consumer expectations, such as effort expectancy. Secondly, we did not assess consumer satisfaction with bank automation. Future studies could add value by examining how cognitive schemas' impact on performance expectancy might translate into consumer satisfaction or dissatisfaction, thus enriching the discrepancy theory framework.

Finally, our analysis was limited to Italy. Although this context is relevant due to its low adoption rates for digital financial services and its high individualism score, which underscores the importance of the performance expectancy construct, it restricts the generalizability of our findings. Future research could broaden the analysis to include other countries to gain a more comprehensive understanding of the influence of cognitive schema and cultural values on digital financial services adoption.

References

Aburayya, A., Al Marzouqi, A.M., Alawadhi, D.A.M., Abdouli, F. and Taryam, M. (2020), "An empirical investigation of the effect of employees' customer orientation on customer loyalty through the mediating role of customer satisfaction and service quality", *Management Science Letters*, Vol. 10 No. 10, pp. 2147-2158.

Akhlaq, A. and Ahmed, E. (2013), "The effect of motivation on trust in the acceptance of internet banking in a low income country", *International Journal of Bank Marketing*, Vol. 31, pp. 115-125.

Alalwan, A.A., Dwivedi, Y.K. and Rana, N.P. (2017), "Factors influencing adoption of mobile banking by Jordanian bank customers: extending UTAUT2 with trust", *International Journal of Information Management*, Vol. 37, pp. 99-110.

Ambuehl, S., Bernheim, B.D. and Lusardi, A. (2014), "Evaluating deliberative competence: a simple method with an application to financial choice", NBER Working Papers 20618, National Bureau of Economic Research, Inc.

American Banking Association (2023), "National survey: bank customers use mobile apps more than any other channel to manage their accounts".

Andreou, P.C. and Anyfantaki, S. (2021), "Financial literacy and its influence on internet banking behavior", *European Management Journal*, Vol. 39 No. 5, pp. 658-674, doi: 10.1016/j.emj.2020.12.001.

Araujo, T., Helberger, N., Kruikemeier, S. and de Vreese, C.H. (2020), "In AI we trust? Perceptions about automated decision-making by artificial intelligence", *AI and Society*, Vol. 35, pp. 611-623, doi: 10.1007/s00146-019-00931-w.

Aydin, A.E. and Akben Selcuk, E. (2019), "An investigation of financial literacy, money ethics and time preferences among college students: a structural equation model", *International Journal of Bank Marketing*, Vol. 37 No. 3, pp. 880-900, doi: 10.1108/IJBM-05-2018-0120.

Bahadur, W., Khan, A.N., Ali, A. and Usman, M. (2020), "Investigating the effect of employee empathy on service loyalty: the mediating role of trust in and satisfaction with a service employee", *Journal of Relationship Marketing*, Vol. 19 No. 3, pp. 229-252.

Bank for International Settlements (2021), "Fintech and the digital transformation of financial services: implications for market structure and public policy", BIS Papers No 117, July 2021.

Baptista, G. and Oliveira, T. (2016), "A weight and a meta-analysis on mobile banking acceptance research", *Computers in Human Behavior*, Vol. 63, pp. 480-489.

Berger, B., Adam, M., Rühr, A. and Benlian, A. (2021), "Watch me improve—algorithm aversion and demonstrating the ability to learn", *Business and Information Systems Engineering*, Vol. 63, pp. 55-68, doi: 10.1007/s12599-020-00678-5.

Blut, M., Chong, A., Tsiga, Z. and Venkatesh, V. (2022), "Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): challenging its validity and charting A research agenda in the red ocean", *Journal of the Association for Information Systems*, Vol. 23 No. 1, pp. 13-95, doi: 10.17705/1jais.00719.

Bongini, P. and Cucinelli, D. (2019), "University students and retirement planning: never too early", *International Journal of Bank Marketing*, Vol. 37 No. 3, pp. 775-797.

Boush, D.M. and Loken, B. (1991), "A process -tracing study of brand extension evaluation", *Journal of Marketing Research*, Vol. 28 No. 1, pp. 16-28.

Castillo, D., Canhoto, A.I. and Said, E. (2021), "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, doi: 10.1080/02642069.2020.1787993.

Cheng-Xi Aw, E., Zha, T. and Hui-Wen Chuah, S. (2023), "My new financial companion! Non-linear understanding of robo-advisory service acceptance", *The Service Industries Journal*, Vol. 43 Nos 3-4, pp. 185-212, doi: 10.1080/02642069.2022.2161528.

Chou, S.-Y., Lin, C.-W., Chen, Y.-C. and Chiou, J.-S. (2023), "The complementary effects of bank intangible value binding in customer robo-advisory adoption", *International Journal of Bank Marketing*, Vol. 41 No. 4, pp. 971-988, doi: 10.1108/IJBM-08-2022-0392.

Cui, Y.(G.) (2022), "Sophia Sophia tell me more, which is the most risk-free plan of all? AI anthropomorphism and risk aversion in financial decision-making", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1133-1158, doi: 10.1108/IJBM-09-2021-0451.

Deloitte (2019), "Robots are here", *The Rise of Robo-Advisers in Asia Pacific*, available at: https://www2.deloitte.com/id/en/pages/financial-services/articles/robo-advisers-asia-pacific.html

Dietvorst, B.J., Simmons, J.P. and Massey, C. (2015), "Algorithm aversion: people erroneously avoid algorithms after seeing them err", *Journal of Experimental Psychology: General*, Vol. 144 No. 1, pp. 114-126, doi: 10.1037/xge0000033.

di Salvatore, A., Franceschi, F., Neri, A. and Zanichelli, F. (2018), "Measuring the financial literacy of the adult population: the experience of Banca d'Italia", *Questioni di Economia e Finanza. (Banca d'Italia)*, available at: https://www.bancaditalia.it/pubblicazioni/qef/2018-0435/QEF_435_18.pdf

Donepudi, P. (2017), "Machine learning and artificial intelligence in banking", *Engineering International*, Vol. 5 No. 2, pp. 83-86.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019), "Artificial intelligence for decision making in the era of big data—evolution, challenges and research agenda", *International Journal of Information Management*, Vol. 48, pp. 63-71, doi: 10.1016/j.ijinfomgt.2019.01.021.

Dumicic, K., Casni, A.C. and Palic, I. (2015), "Multivariate analysis of determinants of Internet banking use in European Union countries", *Central European Journal of Operations Research*, Vol. 23 No. 3, pp. 563-578.

Dzindolet, M.T., Pierce, L.G., Beck, H.P. and Dawe, L.A. (2002), "The perceived utility of human and automated aids in a visual detection task", *Human Factors*, Vol. 44, pp. 79-97.

Eurostat (2023), *Eurostat Regional Yearbook*, 2023 ed., Publications Office of the European Union, Luxembourg, doi: 10.2785/243734.

Fan, L. (2022), "Mobile investment technology adoption among investors", *International Journal of Bank Marketing*, Vol. 40 No. 1, pp. 50-67, doi: 10.1108/IJBM-11-2020-0551.

Faul, F., Erdfelder, E., Lang, A.G. and Buchner, A. (2007), "G* Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences", *Behavior Research Methods*, Vol. 39 No. 2, pp. 175-191, doi: 10.3758/BF03193146.

Faul, F., Erdfelder, E., Buchner, A. and Lang, A.G. (2009), "Statistical power analyses using G* Power 3.1: tests for correlation and regression analyses", *Behavior Research Methods*, Vol. 41 No. 4, pp. 1149-1160, doi: 10.3758/BRM.41.4.1149.

Filotto, U., Caratelli, M. and Fornezza, F. (2021), "Shaping the digital transformation of the retail banking industry. Empirical evidence from Italy", *European Management Journal*, Vol. 39 No. 3, pp. 366-375, doi: 10.1016/j.emj.2020.08.004.

Finke, M., Howe, J. and Huston, S. (2017), Old age and the decline of financial literacy, *Management Science,* Vol. 63 No. 1, pp. 213-230, doi: 10.1287/mnsc.2015.2293.

Fiske, S.T. and Linville, P.W. (1980), "What does the schema concept buy us?", *Personality and Social Psychology Bulletin*, Vol. 6 No. 4, pp. 543-557, doi: 10.1177/014616728064006.

Fiske, S.T. and Taylor, S.E. (1991), *Social Cognition*, Random House, New York.

Flavián, C., Pérez-Rueda, A., Belanche, D. and Casaló, L.V. (2022), "Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness", *Journal of Service Management*, Vol. 33 No. 2, pp. 293-320, doi: 10.1108/JOSM-10-2020-0378.

Fournier, S. (1998), "Consumers and their brands: developing relationship theory in consumer research", *Journal of Consumer Research*, Vol. 24 No. 4, pp. 343-373.

Fünfgeld, B. and Wang, M. (2009), "Attitudes and behaviour in everyday finance: evidence from Switzerland", *International Journal of Bank Marketing*, Vol. 27 No. 2, pp. 108-128.

Gan, L.Y., Khan, M.T.I. and Liew, T.W. (2021), "Understanding consumer's adoption of financial robo-advisors at the outbreak of the COVID-19 crisis in Malaysia", *Financial Planning Review*, Vol. 4 No. 3, e1127, doi: 10.1002/cfp2.1127.

Grable, J., Heo, W. and Rabbani, A. (2014), "Financial anxiety, physiological arousal, and planning intention", *Journal of Financial Therapy*, Vol. 5 No. 2, pp. 1-18.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2014), *Multivariate Data Analysis: Pearson*, New International ed., Pearson Education, Essex.

Hentzen, J.K., Hoffmann, A., Dolan, R. and Pala, E. (2022), "Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1299-1336.

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.

Kaufmann, E. (2021), "Algorithm appreciation or aversion? Comparing in-service and pre-service teachers' acceptance of computerized expert models", *Computers and Education: Artificial Intelligence*, Vol. 2, 100028, doi: 10.1016/j.caeai.2021.100028.

Kawaguchi, K. (2021), "When will workers follow an algorithm? A field experiment with a retail business", *Management Science*, Vol. 67 No. 3, pp. 1670-1695.

King, B. (2018), *Bank 4.0: Banking Everywhere, Never at a Bank*, John Wiley & Sons, New York.

Kotler, P. and Armstrong, G. (2007), *Principles of Marketing*, 11th ed., Prentice Hall International, Englewood Cliffs, NJ.

Kshetri, N. and Voas, J. (2018), "Blockchain in developing countries", *It Professional*, Vol. 20 No. 2, pp. 11-14.

Lachance, M.-E. and Tang, N. (2012), "Financial advice and trust [report]", *Financial Services Review*, Vol. 21, p. 209, available at: https://link-gale-com.libraryproxy.griffith.edu.au/apps/doc/A312402025/ITOF?u5griffith&sid5summon&xid582ea50df

Lee, J.-C. and Wang, J. (2023), "From offline to online: understanding users' switching intentions from traditional wealth management services to mobile wealth management applications", *International Journal of Bank Marketing*, Vol. 41 No. 2, pp. 369-394, doi: 10.1108/IJBM-08-2022-0345.

Lee, T., Huhmann, B.A. and Yun, T. (2020), "Readability of Korean-Language advertising disclosures moderates knowledge effects", *International Journal of Bank Marketing*, Vol. 38 No. 7, pp. 1421-1440.

Liao, H. and Chuang, A. (2004), "A multilevel investigation of factors influencing employee service performance and customer outcomes", *Academy of Management Journal*, Vol. 47 No. 1, pp. 41-58.

Logg, J.M., Minson, J.A. and Moore, D.A. (2019), "Algorithm appreciation: people prefer algorithmic to human judgment", *Organizational Behaviour and Human Decision Process*, Vol. 151, pp. 90-103, doi: 10.1016/j.obhdp.2018.12.005.

Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019), "Resistance to medical artificial intelligence", *Journal of Consumer Research*, Vol. 46 No. 4, pp. 629-650, doi: 10.1093/jcr/ucz013.

Lou, C., Kang, H. and Tse, C.H. (2022), "Bots vs. humans: how schema congruity, contingency-based interactivity, and sympathy influence consumer perceptions and patronage intentions", *International Journal of Advertising*, Vol. 41 No. 4, pp. 655-684, doi: 10.1080/02650487.2021.1951510.

Lourenço, C.J.S., Dellaert, B.G.C. and Donkers, B. (2020), "Whose algorithm says so: the relationships between type of firm, perceptions of trust and expertise, and the acceptance of financial robo-advice", *Journal of Interactive Marketing*, Vol. 49, pp. 107-124, doi: 10.1016/j.intmar.2019.10.003.

Lusardi, A. and Mitchell, O.S. (2011), "Financial literacy around the world: an overview", *Journal of Pension Economics and Finance*, Vol. 10, pp. 497-508.

Lyons, J.B. and Guznov, S. (2018), "Individual differences in human–machine trust: a multi-study look at the perfect automation schema", *Theoretical Issues in Ergonomics Science*, Vol. 20, pp. 440-458.

Lyons, A. and Kass-Hanna, J. (2021), "A methodological overview to defining and measuring digital financial literacy", *Financial Planning Review*, Vol. 4 No. 2, p. e1113, doi: 10.1002/cfp2.1113.

Madhavan, P. and Wiegmann, D.A. (2007), "Similarities and differences between human–human and human– automation trust: an integrative review", *Theoretical Issues in Ergonomics Science*, Vol. 8 No. 4, pp. 277-301, doi: 10.1080/14639220500337708.

Mahmud, H., Islam, A.K.M.N., Ahmed, S.I. and Smolander, K. (2022), "What influences algorithmic decision-making? A systematic literature review on algorithm aversion", *Technological Forecasting and Social Change*, Vol. 175 C, 121390, doi: 10.1016/j.techfore.2021.121390.

Martins, C., Oliveira, T. and Popovic, A. (2014), Understanding the internet banking adoption: a unified theory of acceptance and use of technology and perceived risk application, *International Journal of Information Management,* Vol. 34, pp. 1-13, doi: 10.1016/j.ijinfomgt.2013.06.002.

Merritt, S.M., Unnerstall, J.L., Lee, D. and Huber, K. (2015), "Measuring individual differences in the perfect automation schema", *Human Factors*, Vol. 57 No. 5, pp. 740-753, doi: 10.1177/0018720815581247.

Migliore, G., Wagner, R., Cechella, F.S. and Liébana-Cabanillas, F. (2022), "Antecedents to the adoption of mobile payment in China and Italy: an integration of UTAUT2 and innovation resistance theory", *Information Systems Frontiers*, Vol. 24, pp. 2099-2122, doi: 10.1007/s10796-021-10237-2.

Mogaji, E., Adeola, O., Hinson, R.E., Nguyen, N.P., Nwoba, A.C. and Soetan, T.O. (2021a), "Marketing bank services to financially vulnerable customers: evidence from an emerging economy", *International Journal of Bank Marketing*, Vol. 39 No. 3, pp. 402-428.

Mogaji, E., Soetan, T.O. and Kieu, T.A. (2021b), "The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers", *Australasian Marketing Journal*, Vol. 29 No. 3, pp. 235-242, doi: 10.1016/j.ausmj.2020.05.003.

Mogaji, E., Farquhar, J.D., van Esch, P., Durodié, C. and Perez-Vega, R. (2022), "Guest editorial: artificial intelligence in financial services marketing", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1097-1101, doi: 10.1108/IJBM-09-2022-617.

Molina-Collado, A., Salgado-Sequeiros, J., Gómez-Rico, M., Aranda García, E. and De Maeyer, P. (2021), "Key themes in consumer financial services research from 2000 to 2020: a bibliometric and science mapping analysis", *International Journal of Bank Marketing*, Vol. 39 No. 7, pp. 1446-1478.

Northey, G., Hunter, V., Mulcahy, R., Choong, K. and Mehmet, M. (2022), "Man vs machine: how artificial intelligence in banking influences consumer belief in financial advice", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1182-1199, doi: 10.1108/IJBM-09-2021-0439.

Nourallah, M. (2023), "One size does not fit all: young retail investors' initial trust in financial robo-advisors", *Journal of Business Research*, Vol. 156 C, 113470.

Parasuraman, R. and Riley, V. (1997), "Humans and automation: use, misuse, disuse, abuse", *Human Factors*, Vol. 39, pp. 230-253.

Pearson, C.J., Geden, M. and Mayhorn, C.B. (2019), "Who's the real expert here? Pedigree's unique bias on trust between human and automated advisers", *Applied Ergonomics*, Vol. 81, 102907, doi: 10.1016/J.APERGO.2019.102907.

Rau, P.P., Li, Y. and Li, D. (2009), "Effects of communication style and culture on ability to accept recommendations from robots", *Computers in Human Behavior*, Vol. 25, pp. 587-595.

Raza, B., St-Onge, S. and Ali, M. (2023), "Frontline employees' performance in the financial services industry: the significance of trust, empathy and consumer orientation", *International Journal of Bank Marketing*, Vol. 41 No. 3, pp. 527-549, doi: 10.1108/IJBM-06-2022-0237.

Riedel, A., Mulcahy, R. and Northey, G. (2022), "Feeling the love? How consumer's political ideology shapes responses to AI financial service delivery", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1102-1132, doi: 10.1108/IJBM-09-2021-0438.

Rossiter, J.R., Percy, L. and Donovan, R.J. (1991), "A better advertising planning grid", *Journal of Advertising Research*, Vol. 31 No. 5, pp. 11-21.

Rühr, A., Berger, B. and Hess, T. (2019), "Can I control my robo-advisor? Trade-offs in automation and user control in (digital) investment management", *Americas Conference on Information Systems*.

Shaikh, A.A. and Karjaluoto, H. (2015), Mobile banking adoption: a literature review, *Telematics and Informatics,* Vol. 32, pp. 129-142, doi: 10.1016/j.tele.2014.05.003.

Sheth, J.N., Jain, V., Roy, G. and Chakraborty, A. (2022), "AI-driven banking services: the next Frontier for a personalised experience in the emerging market", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1248-1271, doi: 10.1108/IJBM-09-2021-0449.

Sjödin, H. and Törn, F. (2006), "When communication challenges brand associations: a framework for understanding consumer responses to brand image incongruity", *Journal of Consumer Behaviour*, Vol. 5 No. 1, pp. 32-42.

Statista (2023a), "Penetration rate of online banking worldwide in 2023, by country". November 15, 2023, *Statista*,available at: https://www.statista.com/forecasts/1169529/online-banking-penetration-by-country

Statista (2023b), "Mobile payments worldwide Statistics report on the market size of different types of mobile payments across the world", *Statista*, available at: https://www.statista.com/study/39303/mobile-payment-usage-worldwide/

Stayman, D.M., Alden, D.L. and Smith, K.H. (1992), "Some effects of schematic processing on consumer expectations and disconfirmation judgments", *Journal of Consumer Research*, Vol. 19 No. 2, pp. 240-255, available at: http://www.jstor.org/stable/2489331

Strömbäck, C., Lind, T., Skagerlund, K., Västfjäll, D. and Tinghög, G. (2017), "Does self-control predict financial behavior and financial well-being?", *Journal of Behavioral and Experimental Finance*, Vol. 14, pp. 30-38, doi: 10.1016/j.jbef.2017.04.002.

Swanson, S.R. and Davis, C.J. (2003), "The relationship of differential loci with perceived quality and behavioral intentions", *Journal of Services Marketing*, Vol. 17 No. 2, pp. 202-219.

Thaler, R.H. (1994), "Psychology and savings policies", *The American Economic Review*, Vol. 84 No. 2, pp. 186-192. available at: http://www.jstor.org/stable/2117826.

Thompson, C.G., Kim, R.S., Aloe, A.M. and Becker, B.J. (2017), "Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results", *Basic and Applied Social Psychology*, Vol. 39 No. 2, pp. 81-90.

Thurman, N., Moeller, J., Helberger, N. and Trilling, D. (2019), "My friends, editors, algorithms, and I: examining audience attitudes to news selection", *Digital Journalism*, Vol. 7, pp. 447-469, doi: 10.1080/21670811.2018.1493936.

Tomić, N. and Todorović, V. (2018), "Challenges of transition to cashless society", in Babić, V. (Ed.), *Contemporary Issues in Economics, Business and Management*, pp. 313-320.

Torres, E.N. and Kline, S. (2013), "From customer satisfaction to customer delight: creating a new standard of service for the hotel industry", *International Journal of Contemporary Hospitality Management*, Vol. 25, pp. 642-659, doi: 10.1108/IJCHM-Dec-2011-0228.

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 Esch, P., Cui, Y. and Jain, S.P. (2021a), "Self-efficacy and callousness in consumer judgments of AI-enabled checkouts", *Psychology and Marketing*, Vol. 38 No. 7, pp. 1081-1100.

van Esch, P., Cui, Y.G. and Jain, S.P. (2021b), "The effect of political ideology and message frame on donation intent during the COVID-19 pandemic", *Journal of Business Research*, Vol. 125, pp. 201-213.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478, doi: 10.2307/30036540.

Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178, doi: 10.2307/41410412.

Vieira, K.M., Delanoy, M.M., Potrich, A.C.G. and Bressan, A.A. (2021), "Financial citizenship perception (FCP) scale: proposition and validation of a measure", *International Journal of Bank Marketing*, Vol. 39 No. 1, pp. 127-146.

Vlaev, I., Chater, N. and Stewart, N. (2009), "Dimensionality of risk perception: factors affecting consumer understanding and evaluation of financial risk", *Journal of Behavioral Finance*, Vol. 10 No. 3, pp. 158-181, doi: 10.1080/15427560903167720.

Wang, M., Cho, S. and Denton, T. (2017), "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, doi: 10.1108/IJBM-04-2015-0046.

Wasan, P. (2018), "Predicting customer experience and discretionary behaviors of bank customers in India", *International Journal of Bank Marketing*, Vol. 36 No. 4, pp. 701-725.

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.

Wieseke, J., Geigenmuller, A. and Kraus, F. (2012), "On the role of empathy in customer-employee interactions", *Journal of Service Research*, Vol. 15 No. 3, pp. 316-331.

Wirtz, J. and Mattila, A. (2001), "Exploring the role of alternative perceived performance measures and needs-congruency in the consumer satisfaction process", *Journal of Consumer Psychology*, Vol. 11 No. 3, pp. 181-192, doi: 10.1207/S15327663JCP1103_04.

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, Y., Weng, Q. and Zhu, N. (2018), "The relationships between electronic banking adoption and its antecedents: a meta-analytic study of the role of national culture", *International Journal of Information Management*, Vol. 40, pp. 76-87, doi: 10.1016/j.ijinfomgt.2018.01.015.

Zhang, L., Pentina, I. and Fan, Y. (2021), "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.

Further reading

Mogaji, E. and Nguyen, N.P. (2022), "Managers' understanding of artificial intelligence in relation to marketing financial services: insights from a cross-country study", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1272-1298, doi: 10.1108/IJBM-09-2021-0440.

Corresponding author

Lucrezia Fattobene can be contacted at: lucrezia.fattobene@uniroma2.it

Appendix
Questionnaire

Socio-demographic and socioeconomics questions

Gender (M, F)

Age

Educational level

a) Primary school
b) Middle school
c) High school
d) University
e) Master's degree and/or post-graduate specialization

Income

a) Less than €9,999
b) Between €10,000 and €24,999
c) Between €25,000 and €39,999
d) More than €40,000

Perfect Automation Schema

High Expectations
5-point Likert scale ranging from *strongly disagree* to *strongly agree*

1. Automated systems have 100% perfect performance
2. Automated systems rarely make mistake
3. Automated systems can always be counted on to make accurate decisions
4. People have NO reason to question the decisions automated systems make

All-or-none thinking
5-point Likert scale ranging from *strongly disagree* to *strongly agree*

1. If an automated system makes an error, then it is broken
2. If an automated system makes a mistake, then it is completely useless
3. Only faulty automated systems provide imperfect results

Performance expectancy of bank automation compared to that of bank employees
5-point Likert scale ranging from *strongly disagree* to *strongly agree*

Compared to the performance of bank employees:

1. Banking automated systems have perfect performance
2. Banking automated systems rarely make errors
3. Banking automated systems are preferable because they minimise errors

Financial Anxiety Scale

Please indicate to what extent do you agree with the statements presented, with scale options ranging from 1 (not at all) to 5 (completely agree)

1. I get unsure by the lingo of financial expert
2. I am anxious about financial and money affairs
3. I tend to postpone financial decisions
4. After making a decision, I am anxious whether I was right or wrong

Financial Security Scale

Please indicate to what extent do you agree with the statements presented, with scale options ranging from 1 (not at all) to 5 (completely agree)

1. I feel secure in my current financial situation
2. I feel confident about my financial future
3. I feel confident about having enough money to support myself in retirement, no matter how long I live

Financial knowledge

1. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

a) More than €102
b) Exactly €102
c) Less than €102
d) Don't know
e) Prefer not to say

2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

a) More than today
b) Exactly the same
c) Less than today
d) Don't know
e) Prefer not to say

3. If interest rates rise, what will typically happen to bond prices?

a) They will rise
b) They will fall
c) They will stay the same
d) There is no relationship between bond prices and the interest rate
e) Don't know
f) Prefer not to say

4. Buying a single company's stock usually provides a safer return than a stock mutual fund.

a) True
b) False
c) Don't know
d) Prefer not to say

5. A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less

a) True
b) False
c) Don't know
d) Prefer not to say

Propensity to internet usage

Which of these best describes your use of the Internet in one month? Please include all use of the Internet, including sending and receiving emails

a) Never or once a month
b) Few times in a month
c) More than five times in a month