Artificial intelligence (AI) in FinTech decisions: the role of congruity and rejection sensitivity

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ARTIFICIAL INTELLIGENCE (AI) IN FINTECH DECISIONS: THE ROLE OF CONGRUITY AND REJECTION SENSITIVITY

Abstract

Purpose - The digital revolution has changed consumer–service provider interaction, spawning a new generation of FinTech. This paper analyzes consumers' reactions to Artificial Intelligence (AI) (vs. human) decisions.

Design/methodology/approach – We tested our predictions by conducting two experimental studies with FinTech consumers (n=503).

Findings – The results reveal that consumers' responses to AI (vs. human) credit decisions depend on the type of credit product. For personal loans, the rejection by an AI provider triggers higher levels of satisfaction compared to a credit analyst. This effect is explained via the perceived role congruity. In addition, the findings reveal that consumers' rejection sensitivity determines how they perceive financial services role congruity.

Originality/value – To the best of the authors' knowledge, this research is the first to jointly examine AI (vs. human) credit decisions in FinTech and role congruity, extending prior research in the field.

Keywords Artificial Intelligence, FinTech, Satisfaction, Role Congruity, Rejection Sensitivity.

Article Type: Research Paper

Introduction

By customizing services and experiences, artificial intelligence (AI) is revolutionizing and reshaping the banking industry (Bleier, Goldfarb, & Tucker, 2021; Campbell et al., 2021; Hoyer et al., 2020; Cukier, 2021; Omoge et al., 2022). AI provides commercial banks with countless benefits, such as enhancing customer experience and providing more personalized services (Financial Times, 2018). As such, the use of AI in FinTech is expected to reach USD 26.67 billion by 2026 (Mordor Intelligence, 2022).

Notably, the digital revolution has affected the relationship between financial firms and consumers (Molina-Collado et al., 2021), creating a new generation of FinTech (financial technology) – i.e., "technology used to provide financial markets a financial product or financial service, characterized by sophisticated technology relative to existing technology in that market." (Knewtson & Rosenbaum, 2020, p. 1044).

In practical terms, large financial firms have invested in delivering a better experience by tracking, personalizing, and optimizing consumers' journeys (Johnson, 2017). Through AI, FinTech has provided services to engage consumers, examine accounts and their financial health, and provide financial advice shaping consumers' expectations (Belanche et al., 2019; Bussmann et al., 2020). The use of AI has developed in key financial services areas such as compliance, lending and credit assessment, and trading and investment decisions (Truby et al., 2020).

In our research, we investigate consumers' reactions toward decisions by AI (vs. humans) under (favorable or unfavorable) outcomes. While recent research suggests that consumers react less favorably to AI (vs. human) (Northey et al., 2022; Longoni, Bonezzi, Morewedge, 2019; Yalcin et al., 2022). Our research suggests that in the context of negative (vs. positive) outcomes, consumers react more positively to AI (vs. human).

By drawing on the psychological attribution (Burnkrant, 1975; Okten & Moskowitz, 2018) and role congruence theory (Fan & Mattila, 2021; Solomon et al., 1985), we theorize and find that individuals will react less favorably to rejections by humans (vs. AI), under negative (vs. positive) outcome valence. Recent consumer research indicates that consumers tend to prefer humans over AI, and such an effect is driven by uniqueness (Longoni et al., 2019; Yalcin et al., 2022). Thus, we expect that rejection by AI will not have the same detrimental impact compared to rejection by a human.

This paper sheds light on using AI in the FinTech context by examining consumers' reactions toward AI (vs. human) credit decisions. In two experimental studies, this research reveals that decision-makers' influence on customer satisfaction varies depending on the credit product. In the case of personal loans (Study 1), rejection by an AI induces higher satisfaction than rejection by a credit analyst. In addition, we show that the perceived role congruity is the underlying mechanism of this effect. In Study 2, we observe that a person's rejection sensitivity influences whether they have a more extreme perception of role congruity (high rejection sensitivity) or a less extreme sense of role congruity (low rejection sensitivity) for both outcomes.

By doing so, our findings have important implications for theory and practice, addressing recent research calls on the unintended consequences of AI (Omoge et al., 2022; Pinochet et al., 2019; Riedel et al., 2022), suggesting that the adoption of AI in financial services shapes customers satisfaction outcomes.

In addition, we extend the role congruity theory (Biddle, 1986; Broderick, 2006; Broderick, 1998; Ho et al., 2020; Solomon et al., 1985) by demonstrating that role congruity mediates the relationship between outcome valence of credit requests (approved vs. rejected) and satisfaction. Finally, we introduce rejection sensitivity by bridging AI studies and FinTech (Berenson et al., 2009; Downey & Feldman, 1996).

Managerially, this research offers practitioners insights into adopting AI in banking by examining automated decision-making, particularly in light of the technological advancements in Fintech powered by AI (Belanche et al., 2019; Bussmann et al., 2020). By recommending which scenarios AI technologies should be further included in credit assessment offers and systems, this research can give novel strategies for the Fintech landscape.

Literature review

Artificial Intelligence and Financial Services

The definition of Artificial Intelligence is not consensus or easy to produce (Kaplan & Haenlein, 2020). Nevertheless, past research has come up with different definitions. Kumar et al. (2016, p. 26) proposed that AI refers to "computational systems that inhabit a complex dynamic environment and continuously perform marketing functions such as (a) dynamic scanning of the environment and market factors including competitors, customers, and firm actions impacting the marketing mix; (b) collaborating and interacting to interpret perceptions, analyzing, learning and drawing inferences to solve problems; and (c) implementing customer-focused strategies that create value for the customers and the firm within the boundaries of trustworthiness and policy". In general, AI involves system-based machines that interact with consumers and provide communication services (Wirtz et al., 2018). In addition, AI systems can self-learn by constantly improving and updating the content (Kumar et al., 2021). Finally, there are different kinds of AI analysis (numeric, text, voice, and image) that are used to analyze customer behavior, allowing for better user experience, demand prediction, personalization, and processes (Shankar, 2018), enhancing the overall experience (Cukier, 2021).

Advancements in data analytics span many industries, including retail (Grewal et al., 2017; Tan et al., 2021), banking (e.g., Kaushik & Rahman, 2015; Omoge et al., 2022), and travel and tourism (Murphy et al., 2019; Pillai & Sivathanu, 2020). Firms today rely on Big Data and AI (Babu et al., 2021; Davenport & Bean, 2018, Payne et al., 2021) and text analysis (Sainaghi et al., 2017) to increase productivity (Makridakis, 2017), to improve the overall experience (Cheng & Jiang, 2020) and tackle problems that humans may find difficult to comprehend (Gupta & Arora, 2017). Such practices allow firms to better tailor consumers' preferences (Puntoni et al., 2021). Indeed, the growth of digital channels has pushed autonomous deployment (Manyika et al., 2017). AI digital assistants simulate human language allowing realistic conversations with consumers, especially compared to the early 2000's assistants (Pantano & Pizzi, 2020, Riikkinen et al., 2018). Moreover, the application of the technology can occur in the back office (for risk assessment, segmentation, recommendation, or process automation), and AI systems usage can have different levels of autonomy: the technology can work as a support tool or completely autonomous – exempting human intervention (de Bellis & Johar, 2020).

The relationship between consumers and AI is complex and nuanced. Among those issues is the increase in privacy concerns (Carmody et al., 2021; Dinev & Hart, 2006; Manikonda et al., 2018; Zarifis et al., 2020), the future of employment, wealth distribution (Lu et al., 2021; Makridakis, 2017), and algorithm bias (Lin & Hsieh, 2007; Melnychenko, 2020) which in turn led to some ethical and legal concerns (Mehrabi et al., 2021; Nadeem et al., 2020; Ntoutsi et al., 2020).

Various financial services have implemented artificial intelligence to improve business processes (Arli et al., 2020). Previous studies in the field presented the AI system as an agent, such as chatbots/assistants (see Appendix A for details). Some examples comprise fraud detection, trading forecasting, and risk modeling (Almirall, 2022; Gartner, 2022; Danske Bank Fights Fraud with Deep Learning and AI, 2018), posing new challenges to AI-based financial services (Giudici et al., 2019).

Satisfaction and Role Congruity

Companies often seek to satisfy consumers by offering differentiated services (Arbore & Busacca, 2009; Vakulenko et al., 2022). Previous research shows that AI in banking contributes to transactional-oriented value propositions rather than relationship-oriented ones (Payne et al., 2021).

AI autonomous systems are already a reality, but there is a lack of understanding of the effect of AI decision-making on consumer outcomes (Chumpitaz & Paparoidamis, 2004; Islam et al., 2021; Teeroovengadum, 2022; Walsh et al., 2004).

We draw on the role congruity theory (Solomon et al., 1985; Wang et al., 2019). The role congruity theory asserts that individuals engage in a range of recognized "roles" that help them and others understand their behavior (Wood & Eagly, 2012). Individuals behave in predictable ways based on the role they are performing and the social norms related to it (Biddle, 1986). These roles represent the current expectations, preconceptions, and conventions that determine whether a person's conduct is congruent or incongruent (Eagly & Karau, 2002). In the marketing context, the role congruence concept suggests that firms also have a part to observe (Broderick, 1998). The fulfillment of this role influences the perception of a firm's performance (Ho et al., 2020; Sharma et al., 2012; Solomon et al., 1985). More specifically, when applied to service encounters, one assumption would be that for achieving service provision success, a good experience, mutual comprehension, and mastery of the roles to be performed by the client and the organization are required (Broderick, 1998).

Role congruity theory has been widely employed in the study of how people are judged in a range of situations, such as the suitability of leadership behaviors (Abraham, 2020), implications of unethical workplace behavior (Mai et al., 2020), or entrepreneur performance in terms of resource acquisition (Wang et al., 2019). For instance, in the banking context, past research has studied the influence of gender role congruity on financing entrepreneurial ventures (Eddleston et al., 2016).

Previous research on consumers' reactions to service failures by AI (vs. human agent) suggests that consumers recognize them as having a similar role, thus increasing role congruity (Ho et al. 2020, Leo et al., 2020). The theory of role congruity emphasizes the importance of congruence between the service provider and their behavior (Miao, Mattila, & Mount, 2011; Solomon et al., 1985), when the behavior is not congruent with the expectation or roles, then it will likely decrease satisfaction (Sharma et al., 2012). Indeed, prior research supports this assumption. Prior research highlights the importance of congruency in service encounters such as store image congruency (O'Cass & Grace, 2008), or between a customer's self-concept and employee image (Jamal & Adelowore, 2008). For instance, research shows that individuals react more favorably to service encounters when the provider might be more congruent with conversational norms (Choi, Liu, & Mattila, 2019). Additionally, research further highlights the importance of service employee–environment fit and congruence (Lim, Lee, & Foo, 2017).

This research extends the role congruity theory to investigate how consumers react to decisions by an algorithm (vs. human). Generally, after requesting a financial service, consumers make interferences about the outcome: approval (vs. rejection), although it is intuitive to argue that negative outcomes would be more dissatisfying despite the nature of the agent. However, in our research, we expect that rejection by a human is less satisfying compared to AI.

Individuals tend to attribute favorable outcomes to themselves (e.g., Yalcin et al., 2022), whereas negative outcomes are usually attributed externally (e.g., the others– Kelley & Michela, 1980). Recent research suggests that consumers tend to favor humans over AI, due to some factors that are associated with uniqueness (Longoni, Bonezzi, Morewedge, 2019). For instance, Yalcin et al. (2022) found that it is easier to attribute positive outcomes when the agent is AI versus human. Put simply, human agents signal uniqueness cues (this offer is for me because I am special) but rejections might sound personal. Thus, we expect that when the outcome is negative, reactions to a human would be less favorable, due to the lay beliefs that human neglected their unique self (Longni et al., 2019), whereas, this effect will not be observed for AI, for example, recent research suggests that consumers attribute less responsibility to AI (vs. human) in context of service failure (Ho et al., 2020). Following this reasoning, we postulate that when the outcome is negative, consumers react less favorably to humans (vs. AI). By doing so, we extend prior studies by showing that the decision-maker type (AI vs. human) affects how consumers react to favorable versus unfavorable outcomes.

Therefore, we propose that consumers attribute less responsibility toward AI (vs. human) for a rejected (vs. approved) credit, impacting their satisfaction. More formally, we hypothesize that:

H1: *The type of response (approved vs. rejected) will impact consumers' satisfaction depending on the decision-maker (AI vs. human).*

H2: *Perceived role congruity will mediate the relationship between the response (approved vs. rejected) and satisfaction.*

Rejection Sensitivity in Banking

We further suggest that rejection sensitivity is a boundary condition for our expected effect. Rejection sensitivity is a cognitive-affect processing disposition that leads to an anxiety response (Downey & Feldman, 1996). According to Romero-Canyas et al. (2010, p.120), it is defined as "*the disposition to anxiously expect, readily perceive, and intensely react to* *rejection*". This anxious expectancy is triggered by situations where both acceptance and rejection are possible, and the answer is overreactive.

Consumers' rejection is rarely discussed in the service literature, thus far, prior research mainly focuses on consumers' decisions to reject or accept service offerings. For example, consumers may be served an unpleasant meal which in turn they decide to return (Gelbrich, Gäthke, & Grégoire, 2014), or how rejection can increase the desire to purchase in the luxury retailing context (Ward & Dahl, 2014). To this end, prior marketing literature falls short of explaining rejection sensitivity.

In the banking context, a study about credit-constrained households indicates that consumers are more reluctant to apply for loans due to fear of rejection (Japelli, 1990). We draw from the rejection sensitivity theory (Ayduk, & Gyurak, 2008), to posit that when individuals are priorly exposed to rejection (Downey et al., 1997), it fosters strengthened sensitivity to future rejection risks, motivating self-protection attempts (Berenson et al., 2009). The rejection sensitivity scale is a compound of rejection/acceptance expectancy and rejection concern, where the rejection concern measures the level of concern/anxiety about the response because of the overreactive response to rejection (Berenson et al., 2009). When rejection is possible, people with high rejection sensitivity are unsure whether they will be accepted or rejected. Nonetheless, the outcome is critical; such instances include cognitive assessments of danger under unknown settings. Conversely, individuals with low rejection sensitivity are less likely to experience heightened defensive motivational system activation in these situations because they consider rejections less likely and significant (Downey et al., 2004). Thus, we propose that:

H3: *Consumers' responses to AI (vs. human) credit decisions will be more extreme for those with high (vs. low) rejection sensitivity.*

Overview of studies

Two studies tested our predictions. In particular, study 1 shows that for personal loans, the rejection by an AI causes less dissatisfaction than rejection by a credit analyst and that the perceived role congruity mediates this effect. The more the bank fulfills its role, the higher the satisfaction. In study 2, the relationship between the outcome, role congruity, and satisfaction is maintained. In this study, we reveal that a person's rejection sensitivity determines if they will have a more extreme perception of role congruity (high sensitivity) or less extreme (lower sensitivity) for both outcomes. As role congruity mediates the relationship between the outcome and the satisfaction, this effect also can be seen in satisfaction.

A minimum of (*N*=60) participants per cell were targeted, excluding responses with missing values or failed attention checks, and additional responses were collected until the target sample size was reached (van Selm & Jankowski, 2006).

Both studies were scenario-based experiments. In the first study, the scenario asked the participants to imagine themselves applying for a personal loan, while in the second study, they were applying for a credit card. In each experiment, the participants were randomly exposed to one of four scenarios that manipulated two conditions 2: decision-maker (credit analyst vs. artificial intelligence) and outcome valence: approved vs. rejected.

		Decision-maker	
		Credit analyst	Artificial intelligence system
Lender's response	Approved	Approved personal loan application by a credit analyst	Approved personal loan application by an AI system
	Rejected	Rejected personal loan application by a credit analyst	Rejected personal loan application by an AI system

Table 1. Conditions of the experimental studies (Study 1 and 2)

Besides the authorization to analyze the participants' data, to ensure only EU inhabitants respond to the survey, the country of residence was asked, as well as a captcha question. To improve the quality of the responses attention checks were performed.

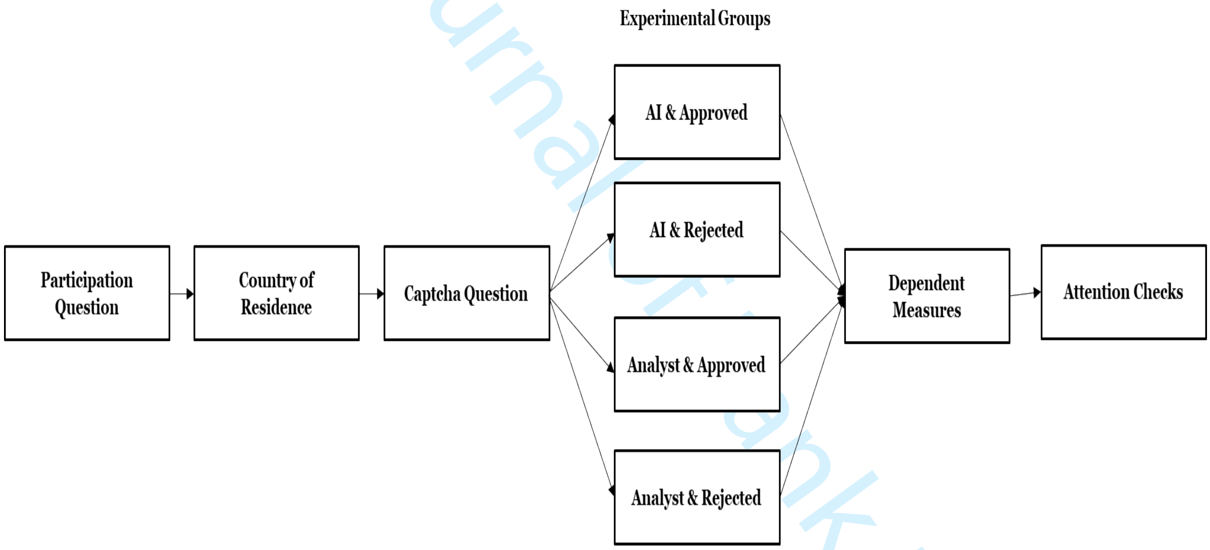

Figure 1. Overview of studies – checkpoints

A test for common method bias for both studies was conducted. To test common method bias, Harman's single factor score was used (Eichhorn, 2014), in which all items were loaded into one common factor. For both study 1 and study 2, the total variance for a single factor is less than 50% (47.01% and 45.46%, respectively). Hence, suggesting that common method bias does not affect our results.

Study 1

This study aims to investigate the joint impact of outcome valence: approval (vs. rejection) and the decision maker: AI (vs. credit analyst). Participants were randomly assigned to one of our four experimental conditions. In the first study, the outcome of a personal loan request and the decision-maker were manipulated to study the impact on satisfaction. Specifically, a scenario-based experiment where participants were asked to imagine themselves in the scenario described. In particular, Study 1 tests the following model:

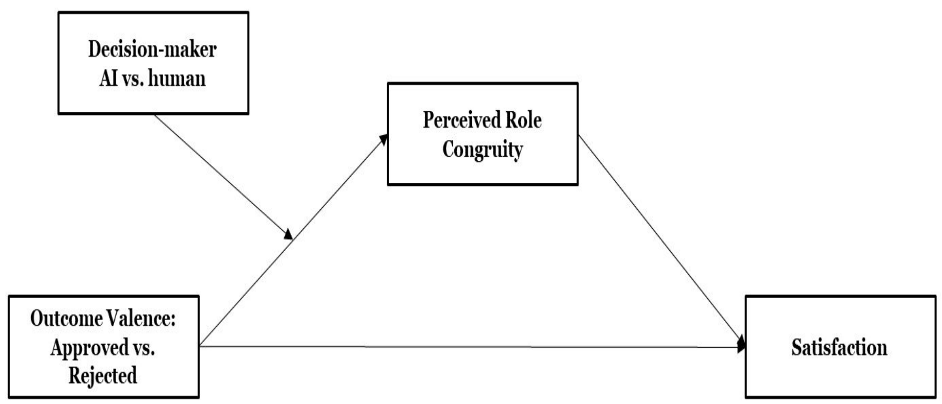

Figure 2. Proposed conceptual model of Study 1

Participants and Design. Two hundred sixty-one FinTech consumers (M_{age}[1]=32.7) were recruited through the online panel, Amazon Mechanical Turk (MTurk). This platform allows hiring people to perform tasks, such as survey participation. The sample consisted of males (72.4%), from 18 to 44 years old

[1] Mage = Mean Age

(84.4%), with an education equivalent to or superior to a bachelor's degree (71.2%), with greater participation from residents in Spain, the UK, and Italy. Before starting the research, the participants were screened for their country of residence. The ones who lived outside the EU were not allowed to continue. The study focused on European Union residents over the age of 18. In the EU, it is mandatory to disclose when a customer is subjected to an automated decision-making process (General Data Protection Regulation, Art. 22, 2018). This particularity makes understanding the implications on EU consumers' perceptions even more pressing.

The procedure, Stimuli, and Measures. The participants had to agree to participate and pass a captcha verification question – to discard eventual bots- and pass one attention check question. Of the 316 participants that started the survey, 261 were able to finish it. On top of it, the security option "Prevent multiple submissions" at Qualtrics was turned on to prevent participants from answering the survey more than once. All the participants that concluded the survey and passed the attention checks were included in the analysis – see Table 1.

Experimental group	*n*
AI system scenario and personal loan approval	67
AI system scenario and personal loan rejection	71
Credit analyst scenario and personal loan approval	62
Credit analyst scenario and personal loan rejection	61
Note: $n =$ 261	

Table 2. Summary of experimental groups

Participants were exposed randomly to four conditions: 2 decision-makers (human vs. AI) x 2: outcome (approval vs. rejection). Participants under the AI condition were instructed to read a definition of AI, then we asked them about their prior experience with AI in banking. The exposition and test questions were presented after the scenario and evaluation.

Then participants responded to our measures. Consumer satisfaction was measured by using items from Levesque & McDougall (1996), and the items of perceived role congruity were adapted from Ho et al. (2020). Both constructs used 7-point scale items (1: Strongly disagree; 7: Strongly agree). The items in satisfaction were highly correlated (α = .91) and were averaged into an index of satisfaction. The same procedure was applied for perceived role congruity (α = .82). There were no missing values for either of the scales.

Next, participants answered if they had already interacted with banks and, if so, what type of AI they had interacted with (Chatbot / Assistant, Investment advice, Simulations of loans and mortgages, Risk assessment, or others).

The internal consistency of a model is validated by Cronbach's alpha - over 0.6 (Ursachi et al., 2015). To assure acceptable indicator reliability, the outer loadings should be above 0.7. Those results validate the use of the latent variables (Bagozzi & Yi, 1988; Gefen, Straub, & Boudreau, 2000; Nunnally, 1978) to test the conceptual model. In addition, we assessed convergent validity and discriminant validity according to Fornell & Larcker, (1981) where all AVE is above 0.5.

	Role Congruity	Satisfaction
Role Congruity	0.899	
Satisfaction	0.774	0.928

Table 3. Fornell-Larcker criterion

Measurement items	Cronbach's alpha	AVE	Average loading	Item Loading	Correlation	p-value	Sum of squares and cross products	Covariance
Satisfaction (adapted from Levesque & McDougall, 1996)	0.911	0.754	0.868		1	-	816.79	3.18
1. How would you rate your overall satisfaction with the experience?				0.838				
2. How would you rate your overall satisfaction with the decision?				0.872				
3. How would you rate the overall satisfaction with the service of this bank?				0.895				
Perceived role congruity (adapted from Ho et al., 2020)	0.825	0.585	0.765		0.758*	2.3E-49	489.80	1.91
1. The bank has fulfilled its role responsibly.				0.841				
2. The bank fulfilled its role as you would have expected.				0.851				
3. The bank fulfilled its obligations to you.				0.841				

*p<0.001
[a] Items measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Table 4. Properties of measurement items

Results and Discussion. A two-way ANOVA reveals a significant interaction between decision-maker and outcome ($F(3, 257) = 4.595$, $p = .033$, $\eta p2 = 0.18$) on satisfaction.

A main effect of the outcome was observed on satisfaction ($M_{approved}$= 5.70, $M_{rejected}$ = 3.07; t(260) =304.42, p < .001). However, a main effect of the agent was not observed (M_{AI}= 5.70, M_{human} = 0.612; t(260) =, p =0.435). A pairwise comparison shows that for the positive outcome, there was no significant difference between subjects in the AI or Human condition (M_{AI} = 5.64, *SD*= 1.011 vs. M_{Human} = 5.75, *SD*=.86, p = .599), contributing to recent studies (Ho et al., 2020).

However, in the negative outcome scenario, when rejected by an AI system, the satisfaction was slight - but significantly – higher than the satisfaction of those rejected by a credit analyst (M_{Human} = 2.80, *SD*= 1.36 vs. M_{AI}=3.33 SD = 1.42, p = .013) - see figure 3.

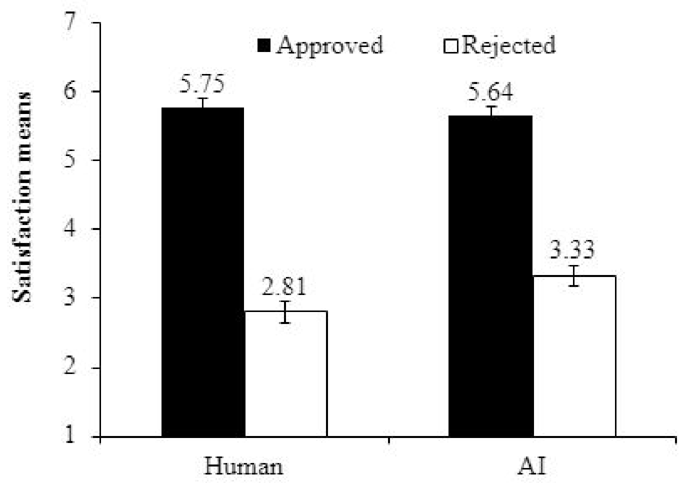

Figure 3. Outcome and satisfaction

This result is counterintuitive because 69.3% of the respondents preferred their credit to be evaluated by a credit analyst (vs. an AI).

Nevertheless, this finding helps bring nuance to the theory (Ho et al., 2020), which was not tested in a negative outcome scenario.

The results could be influenced by the belief that AI is more capable of accurately judging a person's capacity to repay the loan (Batara et al., 2021) or given AI systems' technical skills (Xu et al., 2020).

Mediation Analysis. When the moderated mediation model (see figure 1) was analyzed using PROCESS Model 7 (with 5,000 resamples with replacement; Hayes, 2013), the relationship between the outcome and the perceived role congruity was significantly moderated by the decision-maker (b = 0.75, *SE* = .274, *t* = 2.741, *p* = .007).

The higher the perceived Role Congruity, the higher satisfaction. The low perceived role congruity in the rejection cases ($M_{\text{Rejected}} =$ 3.091 vs. M_{Approved} = 5.695) indicates that even though the firm representative matters, the role is not exclusive to the front office. The institution also has a role in attending to (Broderick, 1998), defined by its expectations through brand, policies, and previous experiences.

Perceived role congruity partially mediates the relationship between outcome and satisfaction in the presence of the moderator with more impact in the human condition (indirect effect = -1.312, *CL*= [-1.720; -.935]) than in the AI condition (indirect effect = -.844, *CL*= [-1.187; -.533]).

Relationship	Direct Effect	Indirect Effect	Confidence Interval	
Lender's response -> Role Congruity -> Satisfaction			Lower Bound	Upper Bound
Human	-1.312	.203	-1.720	-0.935
AI	-.844	.168	-1.187	-0.533

Table 5. Moderated mediation analysis

Study 2

This study complements the first one by analyzing the same relationships for credit cards and introducing a new variable. Credit card is another form of delivery of credit products. In particular, Study 2 tests the following model:

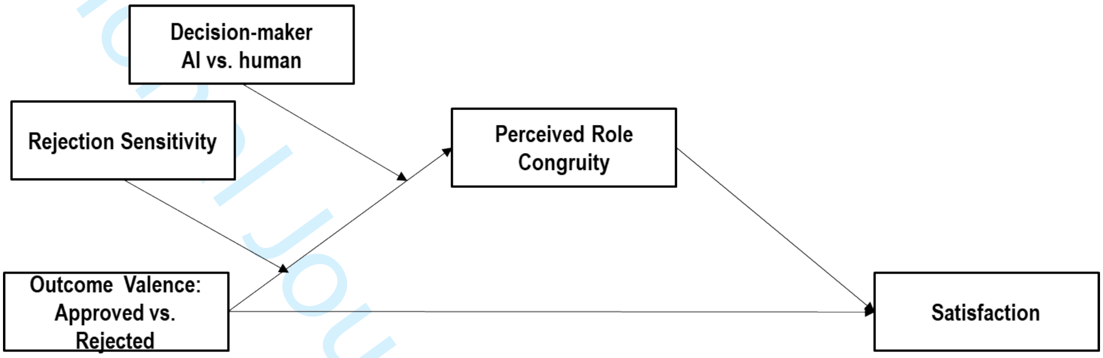

Figure 4.- Proposed Conceptual Model of Study 2

Participants and Design. Two hundred forty-two FinTech consumers (Mage=32.3) who completed the study were recruited through Amazon Mechanical Turk (MTurk). A study 1, participants were EU residents over 18.

Of the 372 participants that started the survey, 242 were able to finish it (Mage=32.3). Participants were primarily male (69%), from 18 to 44 years old (84.3%), with an education equivalent to or superior to a bachelor's degree (66.9%), and with greater participation from residents in Italy and Spain.

The procedure, Stimuli, and Measures. The subjects were exposed randomly to four different scenarios where the decision-maker (human vs. AI) and the outcome valence (approved vs. rejected) were manipulated.

After agreeing to participate and passing the captcha question, the participants were randomly assigned to one of four scenarios. In addition, participants faced an attention check question, the participants who failed had their participation terminated and were not included in the analysis.

Experimental group	*n*
AI system scenario and credit card approval	61
AI system scenario and credit card rejection	60
Credit analyst scenario and credit card approval	61
Credit analyst scenario and credit card rejection	60
Note: *n* = 242	

Table 6.- Summary of experimental groups

Two of the constructs used were satisfaction and perceived role congruity. Both scales used 7-point scale items (1: Strongly disagree; 7: Strongly agree). The items in satisfaction were highly correlated (α = 0.90) and were averaged into an index of satisfaction. The same procedure was applied for Perceived role Congruity (Ho et al., 2020) (α = 0.87). The same items were used as in the first study. There were no missing values for either of the scales.

After the participants answered questions about their rejection sensitivity (adapted from Berenson et al., 2009) with a 6-point scale (1: Very unconcerned, 6: Very concerned), the reliability of the scale was a little below the threshold (Cronbach's α = 0.687). Still, in this study, it was considered acceptable.

	Role Congruity	Rejection Sensitivity	Satisfaction
Role Congruity	0.910		
Rejection Sensitivity	0.151	0.834	
Satisfaction	0.831	0.201	0.919

Table 7. Fornell-Larcker criterion

Measurement items	Cronbach's α	AVE	Average loading	Item Loading	Correlation	p-value	Sum of squares and cross products	Covariance
Satisfaction (adapted from Levesque & McDougall, 1996)	0.904	0.723	0.851		1	-	695.56	2.89
1. How would you rate your overall satisfaction with the experience?				0.864				
2. How would you rate your overall satisfaction with the decision?				0.786				
3. How would you rate the overall satisfaction with the service of this bank?				0.833				
Perceived role congruity (adapted from Ho et al., 2020)	0.871	0.593	0.770		0.791*	4E-53	509.21	2.11
1. The bank has fulfilled its role responsibly.				0.734				
2. The bank fulfilled its role as you would have expected.				0.810				
3. The bank fulfilled its obligations to you.				0.752				
Rejection sensitivity (adapted from Berenson et al., 2009)	0.687	0.580	0.762		-0.193*	0.00258	-103.97	-0.43
1. When you ask your bank for a loan to help you through a difficult financial time, how concerned or anxious would you be over whether or not your bank approves your request?				0.768				
2. When you ask your bank for a credit card to make an expensive purchase you need, how concerned or anxious would you be over whether or not they deny your request?				0.760				

*p<0.001

[a] Items measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

[b] Items measured on a 6-point Likert scale (1 = Not concerned at all, 6 = Very concerned).

Table 8. Properties of measurement items

Results and Discussion. Unlike study 1, and following the study published by Ho et al. (2020), a two-way ANOVA revealed that for credit card requests, the firm's representative does not influence customer satisfaction ($f(238) = 1.334$, $p = .249$). It also does not moderate the relationship between outcome and decision-maker ($b = -0.388$, $t(238) = -1.1549$, $p > 0.05$).

This supports our predictions for this product request. The difference between the impact of the decision-maker could be due to the nature of the products. While a personal loan is merely a credit product, the credit card is also a payment method, with not only interest rates but also monthly or annual fees.

The Satisfaction score, however, continued to be significantly smaller for those who had their credit card request denied in comparison to those who had the request approved ($M_{\text{Rejected}} = 3.058$, $M_{\text{Approved}} = 5.227$, $F(238) = 166.377$, $p < 0.01$).

Moderated Mediation Analysis. Using PROCESS Model 8 (with 5,000 resamples with replacement; Hayes, 2013), we confirmed that the mediation effect of perceived role congruity was significant for the analyzed scenarios. This was a moderated mediation analysis, which confirmed the moderation effect of rejection sensitivity in the relationship between outcome and role congruity ($b = -.347$, $SE = 0.135$, $t(238) = -2.569$, $p = .011$). The relationship between outcome and satisfaction was not moderated, as expected.

Higher rejection sensitivity will lead to increase perceived role congruity upon approval, but it will also drive lower scores when rejected (see figure 4). Low Rejection sensitivity will soften the outcome effect on the perceived role congruity. The indirect effect of the presence of the moderator (at mean level) is -1.368 ($SE = 0.144$, $95\%\ CI = -1.656; -1.088$).

Relationship	Direct Effect	Indirect Effect	Confidence Interval	
Outcome -> Role Congruity -> Satisfaction			Lower Bound	Upper Bound
Low rejection concern	-1.085	0.197	-1.465	-0.706
Average rejection concern	-1.368	0.144	-1.656	-1.088
High rejection concern	-1.651	0.185	-2.023	-1.295

Table 9. Moderated Mediation analysis

This finding indicates that the channel, the technology, and the process are important, but the characteristics of the customer have a significant role in their perceptions of the service. Consumers with a higher rejection sensitivity will have more extreme reactions to request responses. That means greater satisfaction, which could lead to greater loyalty. These consumers represent an opportunity for a long-term relationship, but their pain points must be addressed – for they will also be more dissatisfied by denials.

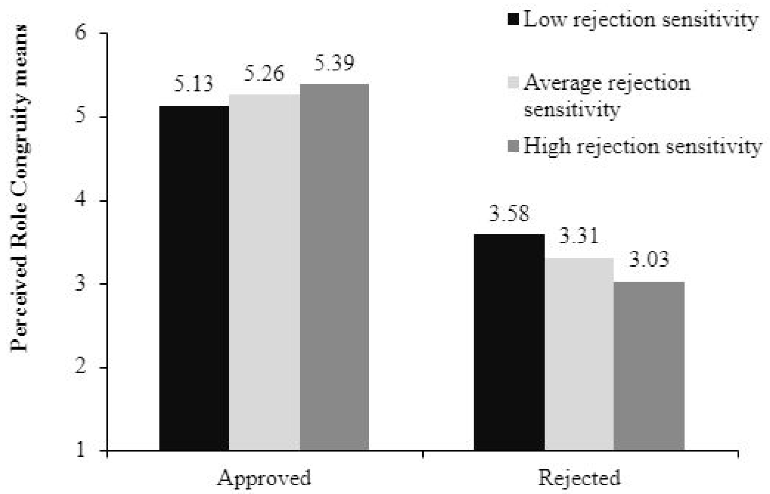

Figure 5. Perceived role congruity vs. Outcome vs. Rejection sensitivity

General Discussion

This research analyzes the effect of AI decision-making on consumers in the banking context. Our findings contribute to the understanding of how decisions by AI (vs. human) can affect consumers' responses. Although recent studies have highlighted the important role of AI on consumer–provider interaction, yet this topic has received limited attention in the marketing literature. Our findings indicate that rejection by an AI trigger a higher level of satisfaction compared to rejection by a credit analyst for personal loans, due to perceived role congruity. In addition, we observed that consumers' responses to AI vs. human credit decisions are more extreme for those with high (vs. low) rejection sensitivity. Our results imply that relationship-oriented banks should pay attention to and be careful when dealing with customers with high rejection sensitivity, while transaction-oriented banks should focus their efforts on the lower rejection segment of customers. Next, we discuss the theoretical contributions and the practical implications of our work.

Theoretical contributions

Our study findings contribute to the literature in at least three significant ways. First, this research extends prior studies on consumers' reactions to decisions by AI (Yalcin et al., 2022), contributing to studies on the use of AI (vs. human) in financial services (Mogaji, Adeola, et al., 2021; Omoge et al., 2022; Riedel et al., 2022). Our research by examining consumers' reactions to AI (vs. human) credit decisions has expanded on automated decision-making on satisfaction to show that AI does not negatively influence customer satisfaction. In our study, we investigate how customers would respond to decisions made by

AI (vs. humans) under (favorable or unfavorable) outcomes. Our research contributes to previous studies (Ho et al., 2020) by showing that consumers hold AI to be less responsible than humans. Hence, we build on earlier research by demonstrating how customers' responses to approve vs. reject results depend on the decision-maker type (AI vs. human).

Secondly, our research extends the role congruity theory (Biddle, 1986; A. Broderick, 2006; A. J. Broderick, 1998; Ho et al., 2020; Solomon et al., 1985) to the FinTech industry. Drawing on the role congruity theory, we fill a gap in research. Besides the past efforts to explore AI autonomous systems, there was a lack of understanding of the effect of AI decision-making on consumers ' perceptions. Considering that satisfaction impacts loyalty (Chumpitaz & Paparoidamis, 2004; Islam et al., 2021; Teeroovengadum, 2022; Walsh et al., 2004), it could harm long-term economic sustainability. However, our study shows that role congruity mediates the relationship between outcome (approved vs. rejected) and customer satisfaction. Our research contributes to previous studies (Ho et al., 2020) by showing that consumers hold AI to be less responsible than humans. Hence, we build on earlier research by demonstrating how customers' responses to approve vs. reject results depend on the decision-maker type (AI vs. human).

Finally, our study introduces rejection sensitivity (Berenson et al., 2009; Downey & Feldman, 1996) in studies about banking and AI by showing that rejecting sensitivity is key in understanding the preference for AI (vs. human). Prior research has generally concentrated on consumers' choices to accept or reject service offerings, and consumer rejection is rarely mentioned in the service literature. In light of this, previous marketing literature does not adequately explain rejection sensitivity. Hence, in our research, we further reveal that the service evaluation is more extreme for those who are already emotionally engaged (high rejection sensitivity) with the outcome than those who are not (low rejection sensitivity).

Practical contributions

With so many options to deploy AI in financial services, it's critical to choose prospective applications based on the business value they can generate. This research has uncovered important practical implications for managers by exploring automated decision-making, especially given the technical breakthroughs of Fintech driven by AI (Belanche et al., 2019; Bussmann et al., 2020). Our research suggests that the impact of the decision-maker on customer satisfaction varies according to the credit product (Cheng & Jiang, 2020b; Payne, Dahl, et al., 2021). As such, for personal loans, the rejection by an AI causes less dissatisfaction than rejection by a credit analyst, and for credit cards, the decision-maker is not relevant. Hence, the strategies used by the Fintech institutions will depend on the type of product provided. As such, we believe this research can provide interesting strategies for the Fintech landscape by suggesting in which circumstances AI technologies should be further incorporated into credit assessment offerings and systems. Additionally, our conclusions offer insights into the relationship between customers and financial services providers. We have shown that the customer journey should accommodate the needs of the high rejection sensitivity segment due to its positive response when approved. Hence, to improve the relationship and social connectedness between customers and providers, relationship-oriented Fintech companies should have more care in delivering the rejection response, including information on what the customer needs to do to have access to credit, highlighting the option of contacting a human representative (which already is mandatory by law; General Data Protection Regulation, Art. 22, 2018), and in case a lower value could be granted, check the customer interest in it. Therefore, Fintech institutions should have a clear communication with their customers on how AI will be used and why.

Finally, we suggest that transaction-oriented financial service providers should focus their efforts on the lower rejection-sensitivity segment by making the journey as quick and straightforward as possible. Thus, among possible strategies are pre-approved small loans that can be accessed anytime, reducing the response time for values that could not be pre-approved, and in case of rejection, highlighting a digital source of information (e.g., Frequently asked question pages or a chatbot). By putting the client and service delivery first, Fintech companies can provide the groundwork for AI deployment and develop a case for why it should be implemented.

Future research and limitations

Despite our contributions, this study has significant shortcomings that can be addressed in future research. Firstly, our research studied the relationship between AI decision-making and satisfaction. Although previous research shows a relationship between satisfaction and loyalty (Chumpitaz & Paparoidamis, 2004; Islam et al., 2021; Teeroovengadum, 2022; Walsh et al., 2004), as this is a new phenomenon, we believe the impact of AI on end loyalty deserves deeper exploration. Therefore, future research could extend the current research and investigate the impact on end loyalty. In addition, future research could be developed around the bank's relationship, which could be developed into relevant system and strategy development.

Future research might also look at whether the present study's findings hold in diverse circumstances, such as different contexts or markets since we only considered residents in the European Union for our studies. As such, other markets can present a different response. Even though we claim decision-making (using AI technology) is not significant or produces less customer satisfaction around credit assessment, there is still further research to be considered generalizable. In addition, our study focuses on Fintech. However, more depth around this subject is needed and could be of interest to future research to compare the present results with a retail banking context. In addition, there may also be room for a new type of orientation centered on AI (vs. human) interactions, which may be tested first in banking environments with a strong presence of Fintech applications. Significant emerging issues, namely, cybersecurity, data privacy, misinformation, or trust, still lack theoretical understanding, especially in regard to AI and customer outcomes.

The present study used scenario-based experiments; however, it could be interesting to explore the topic using simulations. The simulations could also explore the AI delivery presentation, comparing customer response to AI systems presented as a form, wizard, or chatbot.

In addition, future studies could address privacy concerns, bias expectancy/perception, or concerns about employment – which could affect customer satisfaction or even incite backlash movements. Furthermore, although we have advanced the understanding of AI decision-making for consumers, the factor that makes personal loans and credit cards different still demands further investigation. Finally, the application of rejection sensitivity is still incipient and could be explored in future works as well as the extension of the role congruity theory into the use of AI technology with a credit assessment context.

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APPENDIX

Appendix A. Previous studies in the field

Study	Dependent variable	Rejection Sensitivity	Findings
Manser Payne et al., 2018	Usage	No	There is disparity in how digital natives perceive relative advantage between our two dependent variables. The proportional benefit for AI-enabled mobile banking was not substantial, indicating an additional degree of complexity that goes beyond convenient rapid banking.
Belanche et al., 2019	Intention to use	No	Consumers' attitudes towards robot advisors, mass media, and subjective interpersonal norms are determinants for adoption.
Xu et al., 2020	Usage Intention	No	For low-complexity tasks, consumers prefer using AI while preferring human customer service for high-complexity tasks. The perceived problem-solving ability mediated the usage intentions (AI vs. Human).
Daniel Bagana et al., 2021	Behavioral intention	No	Examines AI banking in Indonesia, and future intentions. Also addressed the lack of community recommendation and distrust towards the information provided.
Atwal & Bryson, 2021	Intention do use	No	Among investors willing to use robot-advisory services, perceived risk, perceived usefulness, ease of use, and social influences impact the intention to use.
Mogaji et al., 2021	-	No	In emerging-markets, infrastructural challenges inhibit the adoption of chatbots. Other factors are UI design, trust, security, and capabilities.
Hari et al., 2021	Customer brand engagement Satisfaction	No	Interactivity, time, convenience, compatibility, complexity, observability, and trialability are antecedents of Brand engagement when using AI. The engagement in use will cause brand satisfaction and brand usage intention.

Nguyen et al., 2021	Use intention	No	A Bank's chatbot users' intention of continued use has as its strongest predictors satisfaction, trust, and perceived usefulness.
Amelia et al., 2022	Customer acceptance	No	The study detected five main themes that influence Customer acceptance of frontline service robots (FSR): Utilitarian aspect, social interaction, customer responses towards FSR, Brand perspective, and individual and task heterogeneity.
Rahman et al., 2022	Intention to adopt	No	Customers' AI adoption is significantly influenced by attitude towards AI, perceived usefulness, perceived risk, perceived trust, and subjective norms. In this study, perceived ease of use and awareness were not. For Banks, AI is an essential tool against fraud and risk prevention.
Payne et al., 2021	Assessment of artificial intelligence in mobile banking (AIMB)	No	The customer's role in the value-cocreation process is altered with the introduction of AI in self-service technology channels. AIMB contributes more to transaction-oriented (utilitarian) value propositions than to relationship-oriented (hedonic) value propositions.
Suhartanto et al., 2021	Loyalty	No	Millennial loyalty towards AIMB is significantly determined by Service quality, attitude towards AI, and trust.
Yussaivi et al., 2021	Mobile Banking Usage AI-enabled Mobile Banking Usage	No	Trust is the main determinant of millennial loyalty toward AIMB. Service Quality and attitude were also significant.
Lee & Chen, 2022	AI mobile banking app adoption	No	Through task-technology fit and trust, AI's Intelligence and Anthropomorphism increase users' willingness to adopt AIMB. While both characteristics do not affect perceived risk, Anthropomorphism enhances the users' perceived cost.

Manrai & Gupta, 2022	Behavioral intention to use	No	Trust and subjective norms are key determinants of intention to use AI-based investments. Perceived usefulness, perceived ease of use, and attitude were also significant.
Eren, 2021	Corporate reputation Customer Satisfaction	No	The customer satisfaction of AI Banking users is significantly affected by perceived performance, perceived trust, and corporate reputation. Customer expectation has an indirect positive impact through perceived performance.

Appendix B. Detailed Study Procedures

Study 1

Study 1 used a 2x2 between-subject design (decision-maker: human vs. AI; outcome: approved vs. rejected).

Pre-test

AI can be defined as programmable machines capable of carrying out a complex series of tasks automatically. AI can substitute or assist humans by replicating human actions. Examples of AI application in banking may include but are not limited to chatbots in public websites, home banking or phone bank and investment advice. Have you ever interacted with AI in Banks?

- Yes
- No

What type of AI in Banks have you interacted with?

- Chatbot / Assistant
- Investment advice
- Simulations of loans and mortgages
- Risk assessment
- Other. (Please specify)

Conditions (Adapted from Riedel et al., 2022)

Imagine that you need a personal loan, upon finishing the application at a bank you are informed that it will be evaluated by an artificial intelligence system / a credit analyst.

Three days later, you received a notification that your application was approved / not approved.

Dependent Variable

Satisfaction

Please indicate from 1 to 7 (1=Strongly Disagree, 7= Strongly Agree) to the extent you agree with the following statements.

- How would you rate the overall satisfaction with the experience?
- How would you rate the overall satisfaction with the decision?
- How would you rate the overall satisfaction with the service of this bank?

Note: *items were presented in a randomized order.*

Mediator

Perceived role congruity (adapted from Ho et al., 2020)

Please indicate from 1 to 7 (1=Strongly Disagree, 7= Strongly Agree) to the extent you agree with the following statements.

- The bank has fulfilled its role responsibly.
- The bank fulfilled its role as you would have expected.
- The bank fulfilled its obligations to you.

Note: *items were presented in a randomized order.*

Study 2

Study 2 used a 2x2 between-subject design (decision-maker: human vs. AI; outcome: approved vs. rejected).

Conditions (Adapted from Riedel et al., 2022)

Imagine that you need a credit card, upon finishing the application at a bank you are informed that it will be evaluated by an artificial intelligence system / a credit analyst.

Three days later, you received a notification that your application was approved / not approved.

Dependent Variable

Satisfaction

Please indicate from 1 to 7 (1=Strongly Disagree, 7= Strongly Agree) to the extent you agree with the following statements.

- How would you rate the overall satisfaction with the experience?
- How would you rate the overall satisfaction with the decision?
- How would you rate the overall satisfaction with the service of this bank?

Note: *items were presented in a randomized order*.

Mediator

Perceived role congruity (adapted from Ho et al., 2020)

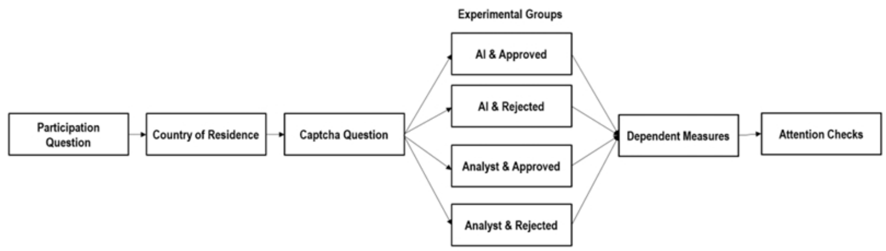
- The bank has fulfilled its role responsibly.
- The bank fulfilled its role as you would have expected.
- The bank fulfilled its obligations to you.

Note: *items were presented in a randomized order.*

Rejection sensitivity (adapted from Berenson et al., 2009)

Please indicate from 1 to 6 (1: Very unconcerned, 6: Very concerned), how concerned do you feel in the following situations:

- When you ask your bank for a loan to help you through a difficult financial time, how concerned or anxious would you be over whether or not your bank approves your request?
- When you ask your bank for a credit card to make an expensive purchase you need, how concerned or anxious would you be over whether or not they deny your request?
- Note: *items were presented in a randomized order.*



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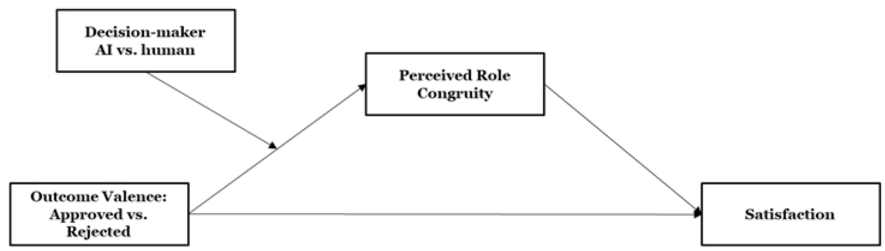

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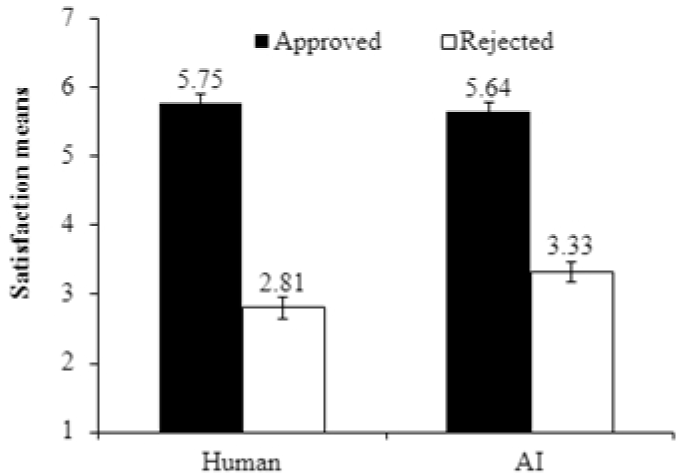

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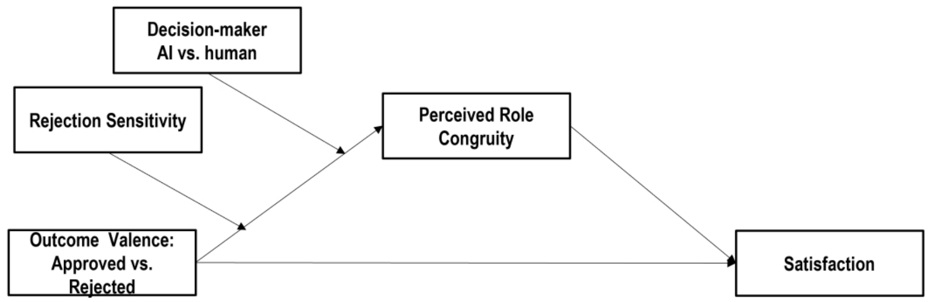

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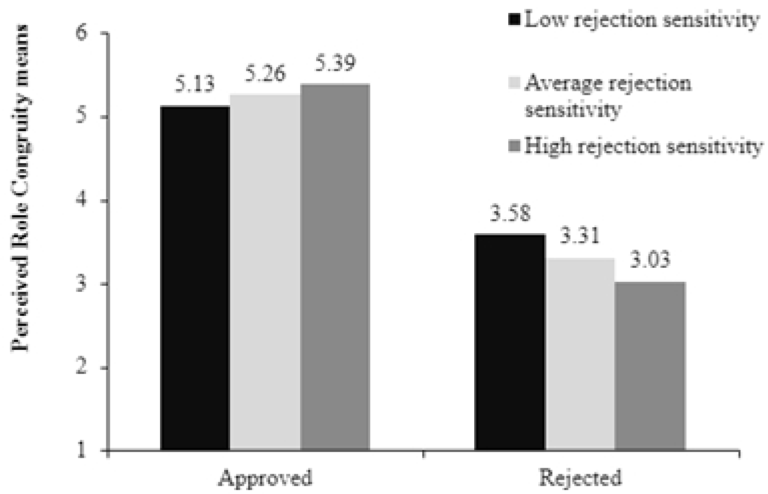

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<table>
<tr><td colspan="2"></td><td colspan="2">Decision-maker</td></tr>
<tr><td colspan="2"></td><td>Credit analyst</td><td>Artificial intelligence system</td></tr>
<tr><td rowspan="2">Lender's response</td><td>Approved</td><td>Approved personal loan application by a credit analyst</td><td>Approved personal loan application by an AI system</td></tr>
<tr><td>Rejected</td><td>Rejected personal loan application by a credit analyst</td><td>Rejected personal loan application by an AI system</td></tr>
</table>

Table 1. Conditions of the experimental studies (Study 1 and 2)

Experimental group	*n*
AI system scenario and personal loan approval	67
AI system scenario and personal loan rejection	71
Credit analyst scenario and personal loan approval	62
Credit analyst scenario and personal loan rejection	61
Note: $n = 261$	

Table 2. Summary of experimental groups

	Role Congruity	Satisfaction
Role Conguity	0.899	
Satisfaction	0.774	0.928

Table 3. Fornell-Larcker criterion

Measurement items	Cronbach's alpha	AVE	Average loading	Item Loading	Correlation	p-value	Sum of squares and cross products	Covariance
Satisfaction (adapted from Levesque & McDougall, 1996)	0.911	0.754	0.868		1	-	816.79	3.18
1. How would you rate your overall satisfaction with the experience?				0.838				
2. How would you rate your overall satisfaction with the decision?				0.872				
3. How would you rate the overall satisfaction with the service of this bank?				0.895				
Perceived role congruity (adapted from Ho et al., 2020)	0.825	0.585	0.765		0.758*	2.3E-49	489.80	1.91
1. The bank has fulfilled its role responsibly.				0.841				
2. The bank fulfilled its role as you would have expected.				0.851				
3. The bank fulfilled its obligations to you.				0.841				

*p<0.001
[a] Items measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Table 4. Properties of measurement items

Relationship	Direct Effect	Indirect Effect	Confidence Interval	
Lender's response -> Role Congruity -> Satisfaction			Lower Bound	Upper Bound
Human	-1.312	.203	-1.720	-0.935
AI	-.844	.168	-1.187	-0.533

Table 5. Moderated mediation analysis

Experimental group	n
AI system scenario and credit card approval	61
AI system scenario and credit card rejection	60
Credit analyst scenario and credit card approval	61
Credit analyst scenario and credit card rejection	60
Note: n = 242	

Table 6.- Summary of experimental groups

	Role Congruity	Rejection Sensitivity	Satisfaction
Role Congruity	0.910		
Rejection Sensitivity	0.151	0.834	
Satisfaction	0.831	0.201	0.919

Table 7. Fornell-Larcker criterion

Measurement items	Cronbach's α	AVE	Average loading	Item Loading	Correlation	p-value	Sum of squares and cross products	Covariance
Satisfaction (adapted from Levesque & McDougall, 1996)	0.904	0.723	0.851		1	-	695.56	2.89
1. How would you rate your overall satisfaction with the experience?				0.864				
2. How would you rate your overall satisfaction with the decision?				0.786				
3. How would you rate the overall satisfaction with the service of this bank?				0.833				
Perceived role congruity (adapted from Ho et al., 2020)	0.871	0.593	0.770		0.791*	4E-53	509.21	2.11
1. The bank has fulfilled its role responsibly.				0.734				
2. The bank fulfilled its role as you would have expected.				0.810				
3. The bank fulfilled its obligations to you.				0.752				
Rejection sensitivity (adapted from Berenson et al., 2009)	0.687	0.580	0.762		-0.193*	0.00258	-103.97	-0.43
1. When you ask your bank for a loan to help you through a difficult financial time, how concerned or anxious would you be over whether or not your bank approves your request?				0.768				
2. When you ask your bank for a credit card to make an expensive purchase you need, how concerned or anxious would you be over whether or not they deny your request?				0.760				

*p<0.001
[a] Items measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).
[b] Items measured on a 6-point Likert scale (1 = Not concerned at all, 6 = Very concerned).

Table 8. Properties of measurement items

Relationship	Direct Effect	Indirect Effect	Confidence Interval	
Outcome -> Role Congruity -> Satisfaction			Lower Bound	Upper Bound
Low rejection concern	-1.085	0.197	-1.465	-0.706
Average rejection concern	-1.368	0.144	-1.656	-1.088
High rejection concern	-1.651	0.185	-2.023	-1.295

Table 9. Moderated Mediation analysis

Study	Dependent variable	Rejection Sensitivity	Findings
Manser Payne et al., 2018	Usage	No	There is disparity in how digital natives perceive relative advantage between our two dependent variables. the proportional benefit for AI-enabled mobile banking was not substantial, indicating an additional degree of complexity that goes beyond convenient rapid banking.
Belanche et al., 2019	Intention to use	No	Consumers' attitudes towards robot advisors, mass media, and subjective interpersonal norms are determinants for adoption.
Xu et al., 2020	Usage Intention	No	For low-complexity tasks, consumers prefer using AI while preferring human customer service for high-complexity tasks. The perceived problem-solving ability mediated the usage intentions (AI vs. Human).
Daniel Bagana et al., 2021	Behavioral intention	No	Examines AI banking in Indonesia, and future intentions. Also addressed the lack of community

			recommendation and distrust towards the information provided.
Atwal & Bryson, 2021	Intention do use	No	Among investors willing to use robot-advisory services, perceived risk, perceived usefulness, ease of use, and social influences impact the intention to use.
Mogaji et al., 2021	-	No	In emerging-markets infrastructural challenges inhibit the adoption of chatbots. Other factors are UI design, trust, security, and capabilities.
Hari et al., 2021	Customer brand engagement Satisfaction	No	Interactivity, time, convenience, compatibility, complexity, observability, and trialability are antecedents of Brand engagement when using AI. The engagement in use will cause brand satisfaction and brand usage intention.
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			of frontline service robots (FSR): Utilitarian aspect, social interaction, customer responses towards FSR, Brand perspective, and individual and task heterogeneity.
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Payne et al., 2021	Assessment of artificial intelligence in mobile banking (AIMB)	No	The customer's role in the value-cocreation process is altered with the introduction of AI in self-service technology channels. AIMB contributes more to transaction-oriented (utilitarian) value propositions than to relationship-oriented (hedonic) value propositions.
Suhartanto et al., 2021	Loyalty	No	Millennial loyalty towards AIMB is significantly determined by Service

			quality, attitude towards AI, and trust.
Yussaivi et al., 2021	Mobile Banking Usage AI-enabled Mobile Banking Usage	No	Trust is the main determinant of millennial loyalty toward AIMB. Service Quality and attitude were also significant.
Lee & Chen, 2022	AI mobile banking app adoption	No	Through task-technology fit and trust, AI's Intelligence and Anthropomorphism increase users' willingness to adopt AIMB. While both characteristics do not affect perceived risk, Anthropomorphism enhances the users' perceived cost.
Manrai & Gupta, 2022	Behavioral intention to use	No	Trust and subjective norms are key determinants of intention to use AI-based investments. Perceived usefulness, perceived ease of use, and attitude were also significant.
Eren, 2021	Corporate reputation Customer Satisfaction	No	The customer satisfaction of AI Banking users is significantly affected by perceived performance, perceived trust, and corporate reputation.

			Customer expectation has an indirect positive impact through perceived performance.

Table 1.- Previous studies in the field which presented the AI system as an agent (chatbot/assistant)