WHY BORROWERS ADOPT AI-ENABLED LOAN SCHEME: ROLE OF TRUST FROM THE ELABORATION LIKELIHOOD MODEL PERSPECTIVE

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ABSTRACT

Despite the rapid growth of AI-enabled recommendations, encouraging borrowers to adopt recommendations in AI-enabled loan recommendation service (AI-LRS) remains a challenge. Based on the elaboration likelihood model and trust transfer theory, this study develops a research model to investigate the factors and internal mechanisms that influence borrowers' intention to adopt recommended loan scheme. A scenario-based survey was conducted to gather 496 valid samples, and structural equation modeling was used to test the model. The results show that both central cues (loan scheme quality, reputation of lending institution, and structural assurance) and peripheral cues (social influence and trust propensity) positively impact borrowers' trust in AI-LRS platform. Additionally, loan scheme quality, reputation of lending institution, and trust propensity are positively associated with borrowers' trust in loan scheme. Moreover, trust in AI-LRS platform positively influences trust in loan scheme, and both types of trust significantly increase adoption intention. Notably, repayment pressure negatively moderates the relationship between trust in loan scheme and adoption intention, while it positively moderates the relationship between trust in AI-LRS platform and adoption intention.

Keywords: AI-enabled recommendation; Trust, Recommendation adoption; Elaboration likelihood model

1. Introduction

Since the turn of the century, advancements in artificial intelligence (AI) have fundamentally transformed how traditional service providers create business and economic value (Longoni & Cian, 2022). Among these advancements, AI-enabled recommendation services, which offer personalized product or solution suggestions based

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on user preferences and interactions, have grown rapidly during the COVID-19 pandemic (Ebrahimi et al., 2022). One emerging application of AI-enabled recommendation services is loan recommendation.

AI-enabled loan recommendation service (AI-LRS) utilizes borrowers' information, including credit histories, loan amounts, repayment plans, and other relevant details, to determine their preferences. These preferences are then processed through automated algorithms to provide personalized loan schemes for each borrower (Wang & Benbasat, 2016). Recently, AI-LRS has become popular. Several credit service platforms, like JD Finance, Upstart, and Rong360, have incorporated AI-LRS into their loan advisory solutions. By replacing traditional loan application processes with AI-enabled matching, AI-LRS has become an integral part of the credit value chain (Trivedi, 2020). As an information intermediary, AI-LRS collaborates with thousands of lending institutions to provide search, recommendation, and application services for loan schemes to millions of borrowers. AI-LRS is characterized by diverse loan offerings, minimal credit knowledge requirements, no need for human intervention, and real-time responsiveness to market dynamics (Dinev & Hart, 2006; Ge et al., 2021). Borrowers can request loan recommendations from AI-LRS anytime and anywhere, rather than downloading multiple apps to collect loan information. AI-LRS is effective in transforming previously fragmented borrowing populations, including small funds or unprofitable "long tail borrowers", into new "rich mines" (Sreepada & Patra, 2020).

In the context of AI-LRS, borrowers' intention to adopt recommended loan schemes is crucial to the success of these services. Therefore, understanding the factors that influence adoption intention is essential. When AI-LRS provides loan recommendations or manages sensitive financial data, it is a situation that heavily relies on trust (Ding et al., 2024). Trust offers psychological assurance about decision quality and outcome reliability, which is especially important in fintech services and loan recommendations (Moin et al., 2015; Roh et al., 2024). The borrower's relationship with AI-LRS differs from their interactions with businesses offering general products or services. Loan recommendations involve financial commitments over time, with significant implications for borrowers' financial well-being (Dowd & Coury, 2006). Such decisions require higher levels of trust and engagement than routine or impulsive purchases (Zarifis & Cheng, 2022). Effective trust management in fintech fosters an engaging and secure environment. When borrowers feel their unique needs are understood and their data is handled responsibly, they are more likely to trust and adopt recommended loan schemes, leading to long-term relationships with AI-LRS.

While prior studies have established a theoretical foundation for understanding trust and AI recommendation adoption in various contexts (Chi et al., 2021; Kim et al., 2021), limited research has examined the trust mechanisms influencing borrowers' adoption of loan schemes recommended by AI-LRS. AI-LRS involves three key participants: the AI-LRS platform providing the recommendations, the recommended loan scheme itself, and the lending institution providing the loan service (Data Yuan, 2017). The relationships among these participants are both significant and complex. This multi-participant structure introduces unique challenges in understanding how trust is established. Most research on AI financial recommendations has focused on a single trust target, such as a technological system or a service provider (Pi et al., 2012; Hildebrand & Bergner, 2021; Zarifis & Cheng, 2024). However, in AI-LRS, trust is influenced by interactions with the AI system and the relationships among participants. For example, a borrower's trust in a recommended loan scheme may depend on the reputation of lending institution, or a borrower may trust the AI-LRS platform but remain skeptical of the recommended loan scheme, leading to hesitation in adopting it. Borrowers evaluate multiple aspects to build trust across different participants rather than relying on a single target. This complexity highlights the limitations of frameworks that consider only one trust target (Shao et al., 2022). To address this gap, this study adopts a multi-participant perspective to better understand trust in AI-LRS. Furthermore, previous research has mainly investigated the factors influencing trust and intentions in AI recommendations from two perspectives: the unique characteristics of AI (e.g., human-like traits) (Benbasat et al., 2020; Chang & Wang, 2023) and general AI recommendation service attributes (e.g., perceived usefulness and ease of use) (Sharma et al., 2022; Wang et al., 2021). However, limited attention has been given to the roles of different participants involved in the recommendation process. This study aims to answer the following two questions:

RQ1: What are the trust targets in AI-LRS from a multi-participant perspective, and how do they influence borrowers' intention to adopt recommended loan schemes?

RQ2: What are the formation mechanisms of the trust targets in AI-LRS?

To address these questions, we develop a research model based on the elaboration likelihood model (ELM) and trust transfer theory. Given the multi-participant nature of AI-LRS and the lack of direct interaction between borrowers and lending institutions on the platform, we focus on two trust targets: trust in loan scheme and trust in AI-LRS platform. We analyze how characteristics of the participants, social networks, and borrower traits contribute to trust formation using four trust reasons: disposition-based trust, institution-based trust, presumption-based trust, and interaction-based trust. The ELM suggests that the persuasiveness in AI-LRS operates through both central and peripheral cues, allowing us to identify loan scheme quality, reputation of lending institution, and structural assurance as central factors, while social influence and trust propensity act as peripheral factors. The ELM provides a theoretical framework for understanding cognitive differences in trust formation. Meanwhile, the four trust reasons encompass various sources of trust, including borrowers, external social networks, and multiple participants in the service. By integrating these theories, we clearly define critical paths for different trust target formations and provide a systematic perspective for understanding trust in AI-LRS. Additionally, we explore the moderating role of repayment pressure on the relationship between trust targets and borrowers' intention to adopt loan scheme. This analysis helps clarify the boundaries within which trust operates. Our findings provide theoretical and practical implications for AI-LRS platforms and lending institutions.

2. Literature Review and Theoretical Foundation

2.1. Trust in AI-LRS

Trust is foundational to financial services and essential for their effective operation. It represents a complex psychological state where one party has confidence in another's actions and behaviors, especially in achieving desired outcomes or goals (Gefen, 2000). With advancements in AI, AI-enabled financial services, such as robo-advisors, AI-LRS, and financial chatbots, allow individuals to manage their financial goals independently, without human intermediaries (Ding et al., 2024). Recently, trust in AI-enabled financial services has gained increasing attention across various contexts. Research consistently highlights that, despite changes in the nature and form of financial services, trust remains a critical mediator in interactions between users and these services (Van der Cruijsen et al., 2023; Pathak & Bansal, 2024).

2.1.1 Trust Target

The AI-LRS platform provides a variety of loan schemes from third-party lending institutions to help borrowers make informed loan decisions. Its recommendation process involves three key steps to identify loan schemes with high approval rates that align with borrowers' needs: First, the platform gathers essential information, including the borrower's personal details, income level, credit score, desired loan amount, and loan term. Next, it uses advanced algorithms to analyze this data, evaluating the borrower's repayment capacity, risk tolerance, and loan urgency. Finally, the platform matches the borrower's profile with available loan schemes, assessing factors such as interest rates, loan amounts, loan terms, approval speed, and approval rates to recommend the most suitable loan schemes (Sachan et al., 2020).

As borrowers increasingly shift from human advisors to AI-LRS platforms, they encounter varying levels of uncertainty. Trust in both AI-LRS platform and its recommended loan schemes significantly influences borrowers' decisions to adopt these recommendations. Traditional trust models often treat trust as a one-dimensional concept, which fails to capture the complexity of financial services (Moin et al., 2015). To address this limitation, researchers have developed multidimensional trust frameworks, such as affective trust, cognitive trust, and models based on the three core elements of trust: competence, integrity, and benevolence (Komiak & Benbasat, 2006; Leong et al., 2021). While these frameworks provide valuable insights, they often view financial services as a single entity, overlooking the distinct roles of individual participants, as summarized in Table 1. In the AI-LRS context, trust involves not only the borrower and the AI-LRS platform but also the recommended loan schemes and lending institutions. Each of these participants plays a significant role in influencing the borrower's trust and decision-making. For example, when evaluating a loan scheme, borrowers may question whether the AI-LRS platform provides unbiased recommendations. In such cases, the reputation of lending institution becomes critical. Borrowers are more likely to trust a recommended loan scheme if it is associated with a reputable or well-regulated lending institution.

This study aims to deepen the understanding of borrowers' trust by adopting a multi-participant perspective. According to Komiak & Benbasat (2004), trust typically involves multiple participants: the product, the entity (e.g., salesperson, website), and the channel (e.g., physical store, online platform). In the AI-LRS context, there are three main participants: the loan scheme, the lending institution, and the AI-LRS platform. Specifically, the AI-LRS platform recommends loan schemes that include key details such as interest rates, loan limits, loan terms, and the name of the lending institution. However, the platform does not manage loan approval or disbursement. These processes are handled independently by the lending institutions. As a result, borrowers typically do not interact directly with lending institutions through the platform, making their trust in lending institutions unclear. In practice, borrowers tend to view the lending institution and its loan scheme as a single entity, incorporating the institution's reputation when assessing trust in other participants. Given this context, this study focuses on borrowers' trust in two key participants: the AI-LRS platform and the recommended loan schemes. Trust in loan scheme reflects borrowers' confidence in the loan scheme (Hsiao et al., 2010), while trust in AI-LRS platform reflects their confidence in the platform's reliability (Bansal et al., 2015).

Table 1: Extant Literature on Trust in Digital Financial Service

Authors	Antecedents of trust	Trust targets	Trust consequences	Research context
(Zarifis & Cheng, 2024)	Human-like interaction, human oversight, transparency and control, accuracy and usefulness, and ease of use and support	Trust generative AI for financial decisions		GenAI for financial questions
(Roh et al., 2024)	System quality, information quality, and service quality	Trust	Perceived security and perceived privacy	Fintech services
(Pathak & Bansal, 2024)	Perceived AI quality, perceived usefulness, and perceived privacy and security	Social trust, cognitive trust, and affective trust	The intention to adopt AI as delegated agents, and the intention to adopt AI as a decision aid	AI financial digital agents
(Kantika et al., 2022)	Perceived security, financial literacy, brand image, and perceived enjoyment	Trust	Adoption of digital bank services	Digital bank services
(Linhart & Stotz, 2022)	Recommending institution, product characteristics, recommending process, and regulation	Trust in retirement products		Pension products recommendation
(Hildebrand & Bergner, 2021)	Interface type	Affective trust	Benevolence attribution and recommendation acceptance	Fintech services
(Talwar et al., 2020)	Perceived information quality, perceived service quality, perceived uncertainty, perceived asset specificity, perceived competence, perceived benevolence, and perceived integrity	Initial trust	Dissatisfaction, perceived usefulness, confirmation	Mobile payment
(Moin et al., 2015)		Institutional trust and dispositional trust	Trusting beliefs	Financial services
(Pi et al., 2012)	Transaction security, prior internet experience, website and company awareness, design of website and interface, navigation functionality, and personalization	Cognitive trust and affective trust	Intention of continuous adoption	Online financial services
(Lin, 2011)		Perceived competence trust, perceived benevolence trust, and perceived integrity trust	Attitude toward adopting mobile banking	Mobile banking

2.1.2 Trust Transfer

When evaluating recommended loan schemes, borrowers often make adoption decisions under incomplete information due to their limited knowledge and decision-making abilities (Wongkitrungrueng & Assarut, 2020). This is particularly significant because the process of evaluating loan schemes often involves trust transfer. According to trust transfer theory, trust in a familiar entity can be transferred to an unfamiliar one under uncertain conditions (Stewart, 2003). Trust transfer has been explored in various contexts, including online recommendation systems, emerging technologies, and e-commerce channels (Shao et al., 2020; Hsu et al., 2022; Wu & Yuen, 2023). In the context of AI recommendations, trust can transfer in several ways: from the recommendation process to the system itself (Cheng et al., 2022), from emotional trust to cognitive trust (Shi et al., 2021), or from a general human-AI system to a specific AI system (macro-to-micro trust transfer) (Lukyanenko et al., 2022). This process happens when individuals perceive a connection between familiar and unfamiliar entities, often based on perceived similarity or proximity (Lee et al., 2021). In this study, we examine the trust transfer process between two trust targets: trust in AI-LRS platform and trust in loan scheme it recommends.

2.2. Antecedents of Trust in AI-LRS

Trust is a complex psychological and social phenomenon influenced by various factors, including personal traits, institutional and environmental attributes, and interactive experiences. According to Kramer (1999) and Wang & Benbasat (2008), there are four main reasons for trust in social and economic contexts: disposition-based trust, institution-based trust, presumption-based trust, and interaction-based trust. Disposition-based trust refers to an individual's inherent tendency to believe in and rely on others. Institution-based trust involves external assurances, such as certifications or legal regulations. Presumption-based trust is rooted in knowledge of role relationships, reflecting trust based on an understanding of the trustee's affiliation with a social or organizational group. Interaction-based trust develops through direct interactions with the trustee (Zucker, 1986). This framework is widely used in studies on new technologies to analyze trust-building processes and their effects on behavioral intentions (Gkinko & Elbanna, 2023; Utz et al., 2023). Considering the unique characteristics of AI-LRS, this study uses four trust reasons to identify specific antecedents of trust.

When an AI-LRS platform recommends loan schemes, it involves a persuasive situation where borrowers evaluate the information provided. The ELM offers a well-established framework to explain how individuals process persuasive messages (Chen et al., 2021). According to ELM, individuals process information through two distinct routes: the central route and the peripheral route (Tam & Ho, 2005). These routes require different levels of cognitive effort (Kitchen et al., 2014). ELM has been widely used to explain changes in trust perceptions, with trust-related factors acting as arguments that influence trust. These factors can be categorized as either central or peripheral cues (Wu & Yuen, 2023; Yang et al., 2006). In the context of AI-LRS recommendations, we apply the ELM to classify trust antecedents, clarify the pathways to trust formation, and enhance our understanding of the adoption process.

2.2.1 Central Routes

The central route involves critically evaluating task-related arguments, weighing their pros and cons, and forming judgments about the target behavior (Greiner & Wang, 2010). Individuals who are highly engaged tend to take the central route and spend significant effort analyzing relevant information. In decision-making, they focus on essential aspects of the decision and information directly related to the outcomes when they invest more cognitive effort (Qahri-Saremi & Montazemi, 2023). When an AI-LRS platform offers personalized loan schemes, borrowers are likely to follow the central route to assess the information related to the recommendation.

AI-LRS operates in a multi-participant environment that includes the AI-LRS platform, lending institutions, and loan schemes. The platform acts as a technical intermediary, processing data and providing personalized loan scheme recommendations. Lending institutions provide the loan funds and services, while loan schemes represent the final recommendations to borrowers. This multi-participant structure creates a complex ecosystem that determines the multi-dimensional nature of trust formation. To better understand how trust develops across different targets, we examine trust antecedents from a multi-participant perspective (Chen et al., 2022). Drawing on interaction-based trust, presumption-based trust, and institution-based trust, we identify three key variables associated with the three participants in AI-LRS: loan scheme quality, structural assurance, and reputation of lending institution. These variables provide crucial information that directly impacts loan decisions and require thoughtful consideration. Since loan schemes significantly affect borrowers' long-term financial interests, borrowers expect them to be accurate and reliable (Ebrahimi et al., 2022). Unlike AI recommendation services that rely heavily on interactive experiences and immediate feedback, borrowers expect AI-LRS to understand their unique needs and provide customized loan schemes. This results in different requirements for interactive trust. High-quality loan schemes that meet borrowers' needs can increase trust (Tsekouras et al., 2022). Compared to other AI recommendation contexts, such as online shopping or social networking, AI-LRS involves highly sensitive financial data, leading to stricter regulatory demands (Pathak & Bansal, 2024). Platforms should establish trust by implementing robust policies and assurances. Structural assurances, such as security protocols, regulatory policies, and privacy protection, effectively address borrowers' concerns about potential risks and build trust (Lu et al., 2021). Additionally, loans are typically long-term economic decisions, with far-reaching impacts compared to short-term consumer purchases. Borrowers tend to place more trust in lending institutions that provide loan services and funding (Zarifis & Cheng, 2022). Since borrowers cannot interact directly with lending institutions through the AI-LRS platform, they assess the trustworthiness of these institutions using publicly available information such as historical performance, credit ratings, and industry recognition. A lending institution's reputation serves as a key indicator of its performance and significantly shapes borrowers' trust (Xu et al., 2024). The combined effects of these three variables provide valuable insights into the trust-building process. For example, when borrowers receive a suitable loan scheme recommendation from a reputable financial institution and are reassured by the AI-LRS platform's robust security measures, their trust increases.

2.2.2 Peripheral Routes

The peripheral route relies on contextual cues to help individuals quickly assess decision-related information (Bhattacherjee & Sanford, 2006). When individuals are less engaged with a decision or have limited cognitive resources, they tend to invest less effort in processing information and rely on external cues to make judgments (Xu & Warkentin, 2020). Loan schemes are often complex, especially for borrowers without financial knowledge or experience (Lusardi & Mitchelli, 2007). In such cases, borrowers may rely on heuristic cues instead of analyzing factors such as interest rates, loan limits, and loan terms.

Peripheral routes typically involve environmental factors, emotional cues, and personal traits to form trust. These routes are characterized by shallow information processing and quick decision-making (Chou et al., 2015; Miller et al., 2021; Sharma et al., 2022). Given that AI is an emerging technology, opinions about AI recommendations play a critical role in influencing trust. Trust propensity refers to an individual's inherent tendency to trust others or systems in a given situation (McKnight et al., 2002). This stable trait enables borrowers to form trust without detailed analysis. Previous research also shows that individuals often rely on feedback or advice from their social networks when making complex or uncertain decisions (Sarkar et al., 2020; Venkatesh et al., 2003). In loan decisions, borrowers may trust an AI-LRS if others around them speak positively about it, without carefully analyzing the details themselves. Therefore, trust propensity and social influence are considered peripheral factors affecting trust. These align with disposition-based trust and interaction-based trust reasons, respectively. They serve as low-effort cues, which are typical of the peripheral route in the ELM. Scholars have emphasized the importance of considering both social networks and personal traits to better understand the adoption of emerging technologies (Shao et al., 2022). Trust propensity reflects the borrowers' intrinsic traits, while social influence represents the effect of external group opinions. Together, they provide a more complete picture of how trust is built through the peripheral route in the AI-LRS context.

Building on the four trust reasons framework, this study integrates three main participant-related variables (loan scheme quality, reputation of the lending institution, and structural assurance), as well as trust propensity as an internal trait and social influence as an external factor into the AI-LRS trust-building framework. Specifically, we classify loan scheme quality, structural assurance, and reputation of lending institution as central route factors, while social influence and trust propensity are treated as peripheral route factors. By integrating the four trust reasons with the ELM, we aim to explore the collective impact of these factors on borrowers' trust in both AI-LRS platform and loan scheme.

3. Research Model and Hypotheses Development

Based on the ELM and four trust reasons, the study first examines how both central and peripheral cues influence borrowers' trust in the AI-LRS context. Additionally, drawing on trust transfer theory, we examine how borrowers' trust in loan scheme and AI-LRS platform affects their intention to adopt the recommended loan scheme. Since borrowing costs can impact adoption decisions, this study includes repayment pressure as a moderating variable. Figure 1 illustrates the proposed theoretical model.

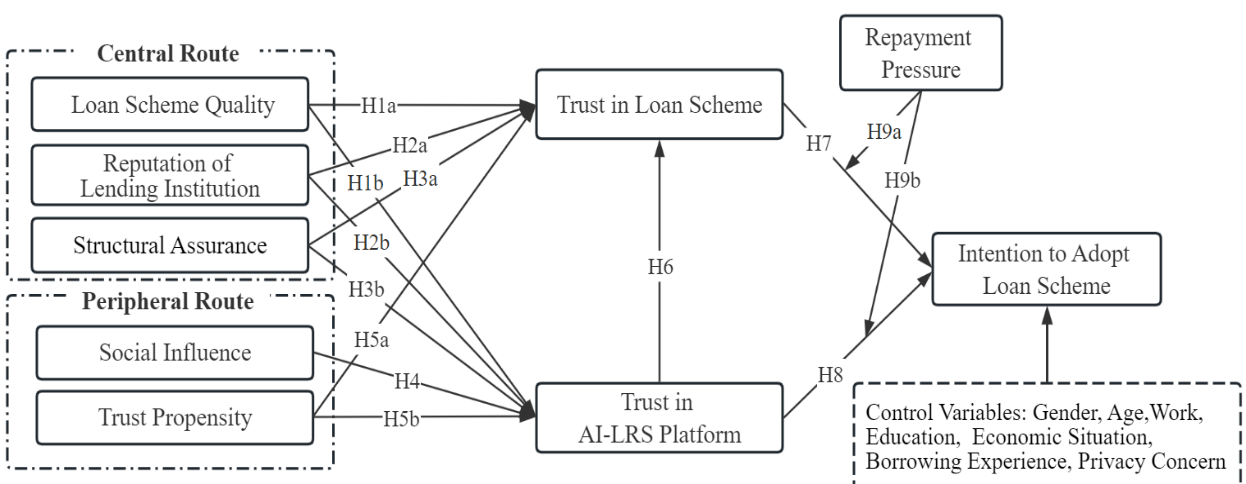


Figure 1: Research Model

Loan scheme quality refers to a borrower's overall assessment of the accuracy, completeness, and relevance of the recommended loan scheme information (Tseng & Wang, 2016). Borrowers have to spend significant effort and time reviewing loan scheme details, as recommendations can vary in quality, from highly accurate and reliable to inaccurate and intentionally deceptive (Kim et al., 2008). Previous studies have demonstrated that higher recommendation quality increases individuals' likelihood of trusting it (Luo et al., 2013). In this study, if borrowers perceive the recommended loan scheme as high quality, they may feel satisfied and develop positive trust in both the recommended loan scheme and the AI-LRS platform (Gao et al., 2021). Conversely, if the recommendation lacks important information or contains inaccuracies, borrowers may find it unreliable and doubt the ability, integrity, and benevolence of the AI-LRS platform (Zhou, 2012). Therefore, high-quality loan schemes are expected to increase trust in both recommended loan scheme and platform. We propose the following hypothesis:

H1: *Loan scheme quality positively impacts trust in loan scheme (H1a) and trust in AI-LRS platform (H1b).*

Reputation of lending institution reflects the general public's impression. It is widely regarded as a central factor in trust formation (Greiner & Wang, 2010; Liang et al., 2019; Ba et al., 2022). Lending institutions with strong reputations can enhance borrowers' confidence in the loan schemes they provide, as a good reputation is built over time through consistent performance (Chen et al., 2018). Positive interactions between a lending institution and past borrowers help reassure new borrowers about the institution's credibility in providing and managing recommended loan schemes (Kim et al., 2008). While maintaining a good reputation typically takes significant time and resources, it can be easily damaged. As a result, reputable lending institutions are less likely to act in ways that could damage borrowers' trust (Jalilvand et al., 2017). Additionally, considering the partnership between the platform and these institutions, a good reputation of lending institutions also positively influences borrowers' trust in the associated AI-LRS platform. Thus, we propose the following hypothesis:

H2: *Reputation of lending institution positively impacts trust in loan scheme (H2a) and trust in AI-LRS platform (H2b).*

Structural assurance refers to the institutional structures, including legislation, contractual rules, and policy guarantees, that are in place to create a safe and reliable environment (Kim & Benbasat, 2009). In this study, official statements from the AI-LRS platform indicate that its services, including loan recommendations, are secure and compliant with laws. Detailed platform policies, such as recommendation strategies, offer clear information about how loan schemes are recommended as expected (Chen et al., 2018). These protective regulations and policy guarantees indicate the professionalism and reliability of the AI-LRS platform in recommending loan schemes (Zhou, 2012). Without structural assurance, trust is limited because borrowers lack institutional guarantees that the platform will not behave opportunistically (Wang & Benbasat, 2008). Meanwhile, borrowers who have experienced an AI-LRS platform with strong structural assurance are more likely to believe that the platform is capable of making reliable recommendations. This further increases borrowers' trust in recommended loan schemes (Bansal et al., 2015). Thus, we propose the following hypothesis:

H3: *Structural assurance positively impacts trust in loan scheme (H3a) and trust in AI-LRS platform (H3b).*

Social influence refers to how much borrowers feel supported or encouraged by others when using AI-LRS platforms (Lyu et al., 2023). Consequently, borrowers' trust in AI-LRS platform may be influenced by others' perspectives on the platform (Beldad & Hegner, 2018). When borrowers see that others recommend the AI-LRS platform and benefit from using it, they are more likely to follow and build trust in it themselves (Gefen, 2000). On the other hand, negative opinions within their social networks can discourage them from using the AI-LRS platform (Roh et al., 2023). Considering that social network opinions are typically about the platform in general and the recommended loan schemes are highly personalized, social influence may limit its impact on borrowers' trust in specific loan schemes. Thus, we hypothesize the following:

H4: *Social influence positively impacts trust in AI-LRS platform.*

Borrowers exhibit varying levels of trust propensity toward AI recommendation technology due to differences in personality traits, cultural backgrounds, and general attitudes toward technology (Miller et al., 2021). Some borrowers naturally trust AI technology for recommendations, while others have a low disposition to trust and may hesitate to rely on it (Sarkar et al., 2020). In the context of AI-LRS platforms, AI recommendation technology provides the technological environment that makes recommendations possible. A high propensity to trust technology encourages borrowers to engage positively with the platform in this environment (Cheung & To, 2017). Consequently, borrowers with a stronger inclination to trust AI recommendation technology are more likely to trust both AI-LRS platform and its recommended loan schemes, while those with lower trust propensity are less likely to do so. Thus, we hypothesize the following:

H5: *Trust propensity positively impacts trust in loan scheme (H5a) and trust in AI-LRS platform (H5b).*

When individuals lack direct experience with a trusted target, they often depend on second-hand information to form trust (Su et al., 2021). Based on trust transfer theory, trust can be transferred from a related and trusted source to the new target (Stewart, 2003). In this study, borrowers may have to assess recommended loan schemes under uncertainty due to their limited ability and knowledge, trust transference may occur when processing these recommendations. Since the loan scheme is recommended by AI-LRS platform, it can be inferred that trust in AI-LRS platform is more likely to influence borrowers' trust in loan scheme (Wongkitrungrueng & Assarut, 2020). If borrowers see the AI-LRS platform as trustworthy, they are more likely to believe that the platform has implemented strict rules for making recommendations, which leads to trust in loan scheme (Xiao et al., 2019). This is especially true when borrowers are unable to evaluate the recommended loan schemes. Thus, we hypothesize the following:

H6: *Trust in AI-LRS platform positively impacts trust in loan scheme.*

Trust plays a crucial role in influencing individuals' behavioral intentions. As Wang & Benbasat (2016) discussed, trust is the key to the ultimate success of recommendation agents. When borrowers seek loan support through an AI-LRS platform, they usually have uncertainties about the validity and reliability of the recommended loan schemes. These uncertainties make borrowers less convinced about their adoption decisions (Zhai et al., 2022). Trust in loan scheme helps increase confidence in the adoption decisions (Chen et al., 2022). Additionally, borrowers face potential risks such as data privacy issues and false recommendations when using loan recommendations. Trust in loan scheme is essential in such a high-risk situation (McKnight et al., 2002). Thus, we hypothesize the following:

H7: *Trust in loan scheme positively impacts intention to adopt loan scheme.*

Trust in service providers generally leads to positive outcomes (Chen et al., 2023; Xiao & Benbasat, 2007). In this study, a trustworthy AI-LRS platform can reduce concerns about opportunistic behavior and enhance borrowers' confidence in their decisions (Luo et al., 2013). When borrowers believe the AI-LRS platform prioritizes their interests and offers valuable recommendations, they are more likely to adopt its recommendations. Conversely, if the AI-LRS platform is perceived as unreliable, borrowers may hesitate to adopt the recommendations due to the potential risk of encountering fake or irrelevant loan schemes (Filieri et al., 2015). Thus, trust in AI-LRS platform plays an important role in predicting borrowers' adoption intention. We hypothesize the following:

H8: *Trust in AI-LRS platform positively impacts intention to adopt loan scheme.*

Trust helps reduce borrowers' uncertainty and encourages them to adopt recommended loan schemes. However, this relationship is influenced by various contextual factors. In this study, key elements of loan schemes, such as interest rates and loan terms, directly affect the monthly repayment amount (Carrasco-Garcés et al., 2021). Higher borrowing costs increase repayment pressure, which poses challenges for borrowers' decisions (Mahmud et al., 2019). Repayment pressure refers to the psychological and financial stress borrowers experience when managing future repayments. It is often perceived as both threatening and complex (Islam et al., 2018). Protection motivation theory (PMT) offers a framework for understanding how individuals perceive threats and adopt protective behaviors (Floyd et al., 2000). Widely applied in different contexts, PMT emphasizes an internal threat assessment process. When faced with a threat, individuals evaluate its severity and their ability to respond, which shapes their motivation to adopt protective behaviors (Tsai et al., 2016). According to PMT, when borrowers experience repayment pressure, they assess the severity of the pressure, their vulnerability, and their ability to cope. If borrowers perceive it as manageable, they are more likely to adopt the loan scheme (White, 1975). However, higher repayment pressure can also lead to more cautious decision-making, as borrowers worry about default and its negative consequences, such as financial strain or reduced quality of life (Khalid et al., 2013). Consequently, even when trust in loan scheme is high, borrowers may approach adoption decisions cautiously. Rational borrowers prefer loan schemes with lower costs, and high repayment pressure can weaken the positive relationship between trust in loan scheme and borrowers' intentions to adopt it.

Research on stress and risk indicates that high repayment pressure heightens borrowers' focus on potential risks (Field et al., 2012; Matos & Krielow, 2019). In such situations, borrowers seek additional information beyond the loan scheme to reduce uncertainty (Phillips-Wren & Adya, 2020). In the multi-participation context of AI-LRS, trust in AI-LRS platform becomes a key way to reduce risk and simplify complex decisions. Borrowers under repayment pressure may question whether the recommended loan scheme aligns with their repayment ability or provides an acceptable balance between benefits and costs. This uncertainty can make them rely more on the trust in AI-LRS platform. According to the coping evaluation component of PMT, borrowers assess both their own ability to manage repayment and the external resources available to them (Vance et al., 2012). High trust in AI-LRS platform enhances borrowers' confidence in the platform's professionalism, the objectivity of its algorithms, and its decision-support capabilities. As a result, borrowers who trust the platform are more likely to believe it can provide accurate risk assessments and recommend suitable loan schemes (Lu et al., 2021). This trust helps borrowers feel more capable of managing repayment pressure and increases their intention to adopt recommended loan schemes. Furthermore, higher repayment pressure can make it more cautious and harder for borrowers to process information effectively (Field et al., 2012). In such situations, they may turn to the AI-LRS platform for decision-making, as trust in the platform offers a safe and straightforward solution (Van Bruggen et al., 1998). While high repayment pressure may generally reduce the likelihood of loan scheme adoption, it can also amplify the positive impact of trust in AI-LRS platform on borrowers' intention to adopt the recommended schemes. Based on this, we hypothesize the following:

H9a: *Repayment pressure negatively moderates the relationship between trust in loan scheme and intention to adopt loan scheme.*

H9b: *Repayment pressure positively moderates the relationship between trust in AI-LRS platform and intention to adopt loan scheme.*

4. Methodology

4.1. Research Design

An online survey was designed to collect data. At the start of the questionnaire, a detailed description of the AI-LRS platform was provided to ensure respondents' understanding of the research context. Participants who expressed no intention to use an AI-LRS platform were excluded. Only those with previous experience or future intentions to engage with an AI-LRS platform were included in the study. Drawing on prior studies (Su et al., 2021), we utilized the recall method to collect perceptual data. For participants with prior experience using an AI-LRS platform, we asked them to recall their most recent borrowing experience in response to the questionnaire.

For respondents who had never used an AI-LRS platform but intended to do so in the future, we employed a scenario-based survey approach, a method commonly used in previous studies to investigate decision-making behaviors. Our study finds this method helpful, as detailed scenario descriptions can enhance respondents' engagement (Caputo, 2016). To better illustrate the platform, we designed prototype diagrams of the AI-LRS platform. Considering that typical loan amounts are around 50,000 CNY (approximately U.S. $7600), which is a reasonable amount within the microfinance range (Data Yuan, 2017), we introduced the following scenario to respondents: "Imagine you are seeking a loan of 50,000 CNY, and there is an AI-LRS platform available to provide loan scheme recommendations." Subsequently, we introduced the process of interacting with the AI-LRS platform to obtain a loan recommendation through images. Respondents were tasked with navigating the information and completing a follow-up survey. Detailed scenario information is available in Appendix 1, with textual instructions near the images. To ensure the authenticity of the scenario, we provided detailed contextual information based on the characteristics and functionalities of a reputable AI-LRS platform in the real world.

4.2. Measurement

Most constructs in the research model were adapted from previous research, with modifications made to align with the context of this study. Among these constructs, repayment pressure is a self-developed construct. To ensure a scientific and rigorous measurement approach, we referenced items from well-established financial stress (Hibbert et al., 2004; Field et al., 2012) and financial efficacy scales (Shim et al., 2019), both of which have been extensively validated in prior studies. All constructs were measured using 5-point Likert scales, ranging from "strongly disagree" (1) to "strongly agree" (5). Appendix 2 summarizes the sources and content of the measurement items. In addition, this study included control variables that could influence borrowers' adoption intention. These variables capture borrower characteristics, including age, education, gender, annual income, past online borrowing experience, and privacy concern (Hong et al., 2023; Silic & Ruf, 2018).

Because the original instruments were in English, we first translated the questions into simplified Chinese and then back-translated them into English. We invited three information systems researchers from prestigious universities and two specialists from lending institutions to review the translations to ensure the items were clear and valid. Any disagreements regarding wording and meaning were discussed and resolved. In addition, a pretest was conducted with 78 individuals who had experience with an AI-LRS platform to revise the questionnaire. After collecting feedback, several minor revisions were made to enhance the items of the questionnaire. Meanwhile, statistical analysis from the pretest indicates that all items met the validity and reliability standards.

4.3. Data Collection

To broaden our data collection efforts, we collaborated with a reputable online survey company, Credamo.com, to help collect data. Specializing in online questionnaire collection, Credamo.com implements various measures to ensure the quality of the survey (Tang & Ning, 2023). We distributed the questionnaire randomly among participants while focusing on ensuring anonymity and confidentiality. Notably, due to regulatory policies on online loans, student samples were excluded from our survey. We also took measures to ensure that each respondent participated only once. After three weeks of data collection, 595 individuals fully completed the questionnaires, with 496 valid responses retained for analysis. Specifically, 36 samples were considered invalid due to excessively short completion times or identical answers, while 63 samples expressing no intention to use the AI-LRS platform were excluded. Demographic characteristics are shown in Table 2. This indicates that younger people and those with middle or low incomes are more likely to use online lending services, consistent with the overall website population (Chang & Wang, 2023).

Table 2: Sample Demographic

Demographic Variables	Description	Frequency	Percentage
Gender	Female	207	41.7
	Male	289	58.3
Age	18-24	143	28.8
	25-34	220	44.4
	35-44	95	19.2
	45-55	38	7.6
Education	High school or below	60	12.1
	Bachelor	329	66.3
	Master or PhD	107	21.6
Per Capita Monthly Spending (RMB)	≤1000	35	7.1
	1001-3000	202	40.7
	3001-5000	161	33.7
	>5000	98	19.6
Work Type	Knowledge workers	330	66.5
	Physical workers	106	21.4
	Unemployed or retired	29	5.8
	Other	31	6.3
Online Borrowing Experience	No	167	33.7
	Yes	329	66.3

5. Data Analyses and Results

We used partial least squares structural equation modeling (PLS-SEM) and SmartPLS 3.3 to test our research model and hypotheses. PLS was chosen for two reasons. First, PLS is suitable for testing complex models with many variables and constructs. Second, it is appropriate for theory exploration with small sample sizes and does not require specific distributional assumptions about the data (Fornell & Bookstein, 1982).

5.1. Measurement Model

Following a two-step data analysis process, we first assessed the reliability and validity of the measurement model. All constructs in the research model are reflective latent variables. We conducted a reliability analysis using Cronbach's alpha and composite reliability (CR) values. As shown in Table 3, Cronbach’s alpha values for all constructs exceed the suggested threshold of 0.7. Additionally, the CR values for each construct are above the minimum suggested value of 0.7 (Nunnally, 1978). All of the evidence demonstrates satisfactory reliability for the measurement instruments.

Convergent validity was assessed through tests of Average Variance Extracted (AVE) values and factor loadings. According to the results presented in Table 3, the AVE value for each construct surpasses the benchmark of 0.5, with all factor loadings being significant and above 0.6. Therefore, convergent validity is supported. To further evaluate discriminant validity, we employed two testing methods: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. According to the Fornell-Larcker criterion, the square root of AVE for each construct should be greater than the inter-construct correlations (Fornell & Larcker, 1982). Additionally, based on the HTMT ratio criterion, the values between constructs should remain below 0.85 (Yusoff et al., 2020). The results in Tables 4 and 5 suggest good discriminant validity.

As this study used self-reported data from a single source, we tested for common method bias (CMB) to enhance the validity of our findings (Podsakoff et al., 2003). To prevent respondents' fatigue and mitigate CMB potential, we counterbalanced the order of items and placed demographic questions at the end of the survey. Meanwhile, Harman’s single-factor test results indicated that the first factor explained 0.38 of the variance, which is below the 0.5 threshold, indicating that CMB is not a primary concern. Furthermore, we examined the correlation matrix of the constructs and found that no correlations (see Table 4) exceeded 0.9, which meets the criterion and suggests no potential bias. Additionally, we employed the variance inflation factor (VIF) to evaluate construct collinearity. The findings showed that the VIF values for all constructs were below 3.3, indicating that multi-collinearity is not a significant issue.

Table 3: Analysis of Measurement Model

Constructs	Items	Mean	S.D.	Loadings	CR	AVE	Cronbach's alpha
Loan Scheme Quality	LSQ1	4.04	0.66	0.804	0.856	0.664	0.747
(LSQ)	LSQ2	4.15	0.80	0.825			
	LSQ3	4.11	0.75	0.816			
Reputation of Lending Institution	RLI1	3.99	0.76	0.837	0.877	0.703	0.790
(RLI)	RLI2	3.98	0.84	0.841			
	RLI3	3.97	0.80	0.838			
Structural Assurance	SA1	4.08	0.75	0.830	0.858	0.669	0.753
(SA)	SA2	4.11	0.76	0.805			
	SA3	4.70	0.75	0.819			
Social Influence	SI1	4.00	0.76	0.710	0.837	0.632	0.713
(SI)	SI2	4.05	0.75	0.812			
	SI3	4.00	0.79	0.857			
Trust Propensity	TP1	3.97	0.73	0.843	0.890	0.669	0.834
(TP)	TP2	4.04	0.80	0.807			
	TP3	4.01	0.75	0.790			
	TP4	4.01	0.76	0.830			
Trust in AI-LRS Platform	TALP1	4.00	0.75	0.859	0.901	0.753	0.836
(TALP)	TALP2	3.98	0.88	0.864			
	TALP3	3.91	0.84	0.880			
Trust in Loan Scheme	TLS1	3.81	0.89	0.899	0.927	0.809	0.882
(TLS)	TLS2	3.77	1.00	0.900			
	TLS3	3.86	0.99	0.900			
Intention to Adopt Loan Scheme	IALS1	3.91	0.75	0.858	0.905	0.760	0.842
(IALS)	IALS2	3.78	0.88	0.874			
	IALS3	3.96	0.91	0.883			
Privacy Concern	PC1	3.17	1.24	0.910	0.946	0.815	0.924
(PC)	PC2	3.08	1.32	0.889			
	PC3	3.07	1.33	0.894			
	PC4	3.16	1.40	0.918			
Repayment Pressure	RP1	2.77	1.09	0.907	0.947	0.818	0.926
(RP)	RP2	2.77	1.27	0.903			
	RP3	2.77	1.27	0.905			
	RP4	2.91	1.33	0.902			

Table 4: Fornell-Larcker Criterion

	LSQ	RLI	SA	SI	TP	TALP	TLS	IALS	PC	RP
LSQ	0.815									
RLI	0.496	0.839								
SA	0.520	0.520	0.818							
SI	0.365	0.403	0.454	0.795						
TP	0.474	0.511	0.454	0.493	0.818					
TALP	0.607	0.616	0.654	0.556	0.622	0.868				
TLS	0.481	0.534	0.430	0.401	0.519	0.573	0.900			
IALS	0.575	0.568	0.545	0.495	0.605	0.699	0.605	0.872		
PC	-0.415	-0.467	-0.357	-0.247	-0.377	-0.517	-0.382	-0.473	0.903	
RP	-0.317	-0.327	-0.249	-0.176	-0.327	-0.373	-0.477	-0.361	0.542	0.839

Table 5: Heterotrait-Monotrait Ratio

	LSQ	RLI	SA	SI	TP	TALP	TLS	IALS	PC	RP
LSQ	-									
RLI	0.640									
SA	0.693	0.672								
SI	0.495	0.403	0.605							
TP	0.600	0.511	0.572	0.629						
TALP	0.767	0.755	0.822	0.699	0.744					
TLS	0.590	0.638	0.525	0.496	0.604	0.666				
IALS	0.722	0.695	0.683	0.626	0.720	0.831	0.702			
PC	0.495	0.545	0.427	0.282	0.429	0.587	0.422	0.534		
RP	0.380	0.381	0.298	0.206	0.370	0.423	0.529	0.407	0.584	-

5.2. Structural Model

We analyzed the path coefficients, path significance, and associated t-values in the structural model. The results presented in Figure 2 indicated a good model fit. Regarding the control variables, borrowers' age and privacy concern exhibited significant negative effects on their intention to adopt loan scheme.

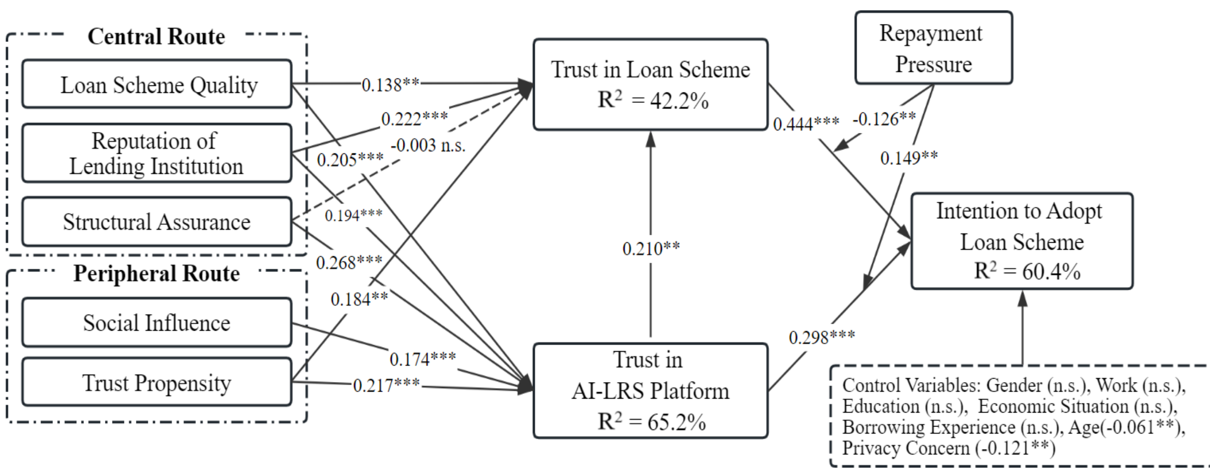
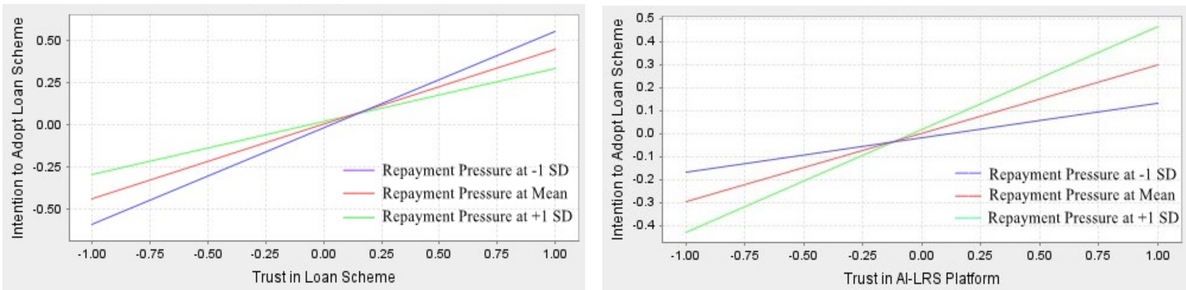


Figure 2: Hypothesis Testing Results

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; n.s. represents not significant.

In the central route, the results show that loan scheme quality ($\beta = 0.138$, $p < 0.01$, H1a supported) and reputation of lending institution ($\beta = 0.222$, $p < 0.001$, H2a supported) significantly influence trust in loan scheme. Additionally, both factors also significantly impact trust in AI-LRS platform ($\beta = 0.205$, $p < 0.001$, H1b supported; $\beta = 0.194$, $p < 0.001$, H2b supported). Structural assurance is significantly related to trust in AI-LRS platform ($\beta = 0.446$, $p < 0.001$, H3b supported), but not to trust in loan scheme ($\beta = -0.003$, $p > 0.05$), thus not supporting H3a. This lack of support could be due to definitional limitations, as structural assurance appears to enhance borrowers' trust in AI-LRS platform rather than in specific recommended loan schemes; it primarily focuses on the reliability of the recommendation environment (Shao et al., 2022). In the peripheral route, social influence significantly contributes to trust in AI-LRS platform ($\beta = 0.174$, $p < 0.001$), supporting H4. Additionally, trust propensity positively influences both trust in loan scheme and trust in AI-LRS platform ($\beta = 0.184$, $p < 0.01$, H5a supported; $\beta = 0.217$, $p < 0.001$, H5b supported). Furthermore, both trust in loan scheme and trust in AI-LRS platform are positively associated with the intention to adopt loan scheme ($\beta = 0.444$, $p < 0.001$, H7 supported; $\beta = 0.298$, $p < 0.001$, H8 supported). Trust in AI-LRS platform significantly impacts trust in loan scheme ($\beta = 0.323$, $p < 0.01$), thus supporting H6.

Borrowers seek to balance the benefits and costs to make an informed decision. While those with high trust in loan scheme are generally more inclined to adopt recommendations, they may reconsider if the loan scheme does not align with their repayment capacity or if its costs outweigh its benefits. Thus, repayment pressure negatively moderates the relationship between trust in loan scheme and intention to adopt it ($\beta = -0.126$, $p < 0.01$). In contrast, when repayment pressure is high, borrowers are more likely to rely on the AI-LRS platform for decision-making, which strengthens the positive relationship between trust in AI-LRS platform and the intention to adopt the recommended loan scheme. Repayment pressure positively moderates this relationship ($\beta = 0.149$, $p < 0.01$), supporting H9. Figure 3 graphically illustrates these relationships at different levels of repayment pressure using mean-centered variables.



(a) (b)

Figure 3: Moderating Effect of Repayment Pressure

5.3. Mediation Analysis

As a further analysis, we examined whether the two different trust targets mediate the relationship between trust antecedents and borrowers' intention to adopt the recommended loan scheme. We conducted a bootstrapping test using SmartPLS 3.3. The results of the bootstrapping mediation test are shown in Table 6. As indicated in the table, the indirect effects of loan scheme quality (Bootstrapping $\beta = 0.061$), reputation of lending institution (Bootstrapping $\beta = 0.099$), and trust propensity (Bootstrapping $\beta = 0.081$) on intention to adopt loan scheme are significantly mediated by trust in loan scheme, with a 95% confidence interval (CI) excluding zero (Liu et al., 2019). Additionally, the indirect effects of loan scheme quality (Bootstrapping $\beta = 0.061$), reputation of lending institution (Bootstrapping $\beta = 0.058$), structural assurance (Bootstrapping $\beta = 0.079$), social influence (Bootstrapping $\beta = 0.052$), and trust propensity (Bootstrapping $\beta = 0.065$) on intention to adopt loan scheme are significantly mediated by trust in AI-LRS platform, with a 95% CI ranging from 0.092 to 0.118.

Table 6: Mediation Tests

Path relationship	Bootstrapping β	95% Confidence interval	
LSQ - TLS - IALS	0.061	0.016	0.105
LSQ - TALP - IALS	0.061	0.029	0.095
RLI - TLS - IALS	0.099	0.046	0.180
RLI - TALP - IALS	0.058	0.024	0.100
SA - TALP - IALS	0.079	0.043	0.118
SI - TALP - IALS	0.052	0.024	0.092
TP - TLS - IALS	0.081	0.032	0.137
TP - TALP - IALS	0.065	0.029	0.111

6. Discussion

This study highlights the significant role of AI-LRS attributes in building borrower trust. Among these attributes, the reputation of lending institution has a slightly stronger impact on trust in loan scheme compared to the loan scheme quality. This might be because reputation is built over time and reflects consistent performance, while the quality of a single loan scheme provides limited information. Structural assurance has the most significant effect on trust in AI-LRS platform. This is likely because structural assurance directly signals the platform's reliability, helping borrowers form an initial judgment of trust. Together with other factors, structural assurance enables a more comprehensive evaluation of the platform, thereby further strengthening trust. Moreover, attributes related to recommendation services have a slightly stronger effect on trust than trust propensity and social influence, which indicates that central cues are more crucial for trust formation than peripheral cues. This finding is consistent with previous research on the ELM (Bhattacherjee & Sanford, 2006; Ren et al., 2023).

This study shows the mediating role of trust in loan schemes and trust in the AI-LRS platform in the relationship between central and peripheral routes and adoption intentions. The empirical results show that these two types of trust operate differently. Specifically, trust in loan scheme mediates the effects of loan scheme quality, the reputation of lending institution, and trust propensity on borrowers' intention to adopt loan scheme. In contrast, trust in AI-LRS platform mediates the effects of loan scheme quality, reputation of lending institution, structural assurance, social influence, and trust propensity on adoption intentions. Both types of trust significantly and positively influence borrowers' intention to adopt the recommended loan scheme. Previous studies have concluded that higher trust increases the likelihood of adopting recommendations (Xiao & Benbasat, 2007). In our study, trust in loan scheme has a stronger influence on adoption intention than trust in AI-LRS platform. This suggests that while borrowers value the platform's reliability, they prioritize whether the specific loan scheme meets their needs. Furthermore, the study reveals a trust transfer process, where trust in AI-LRS platform affects trust in loan scheme. This supports previous studies indicating that borrowers often evaluate the credibility of recommendations based on their trust in a relevant and familiar recommendation service (Chen et al., 2022). The findings highlight the role of AI-LRS platform in reducing uncertainty, building trust, and increasing borrowers' adoption intentions.

This study also identifies the moderating effect of repayment pressure. Specifically, high repayment pressure weakens the positive relationship between trust in loan scheme and adoption intention. However, it strengthens the relationship between trust in AI-LRS platform and adoption intention. According to PMT, borrowers become more cautious under high repayment pressure. Even if they trust the loan scheme, they may hesitate to adopt it due to concerns about repayment defaults. On the other hand, high repayment pressure leads borrowers to seek strategies to manage their financial burdens. If the AI-LRS platform is perceived as a reliable and objective decision-making tool, its importance increases. In such situations, trust in AI-LRS platform can alleviate borrowers' psychological burdens and encourage them to adopt the recommended loan scheme.

Finally, this study examines privacy concern as a control variable and finds that high levels of privacy concern negatively impact borrowers' intention to adopt loan scheme. This negative effect arises from anxiety about potential personal information leaks and security risks (Lyu et al., 2023). Borrowers with high privacy concerns prioritize protecting their personal information and are hesitant to share sensitive details. Consequently, they are less likely to adopt recommended loan schemes that require extensive personal information disclosure.

7. Conclusion

This study developed a theoretical model to explore the factors and mechanisms that influence borrowers' intention to adopt the recommended loan scheme in the context of AI-LRS. A scenario-based survey was conducted in China, and the proposed model was tested using structural equation modeling. The results show that borrower characteristics, lending institution traits, AI-LRS platform characteristics, as well as personal and social factors, collectively influence adoption intention. These effects are mediated by borrowers' trust in loan scheme and trust in AI-LRS platform. Additionally, repayment pressure significantly moderates the relationship between these two types of trust and adoption intention.

7.1. Theoretical Contributions

Our findings have several theoretical implications. First, exploring trust in the context of AI-LRS is valuable. Loan scheme recommendations involve sensitive financial data and long-term economic decisions, which can make borrowers hesitant to rely on AI-LRS unless they trust the system (Zarifis & Cheng, 2022). AI-LRS loan recommendations involve three key participants: the AI-LRS platform, the lending institution, and the recommended loan scheme. Unlike previous studies that typically focus on a single trust target or examine technical services as a whole, this study emphasizes the unique role of a multi-participant ecosystem in AI-LRS. Specifically, we introduce two distinct trust targets: trust in AI-LRS platform and trust in loan scheme. This offers valuable theoretical perspectives that advance trust research in AI-enabled financial decision-making. Additionally, this study explores the process of trust transfer in the AI-LRS context. From a multi-participant perspective, trust can be transferred between different targets, particularly from trust in AI-LRS platform to trust in loan scheme. This finding provides important insights into the psychological and behavioral patterns of individuals when making decisions, thereby enriching our understanding of trust transfer theory.

Second, trust formation in AI-LRS is a multi-dimensional and multi-path process. To provide a comprehensive understanding, we incorporate four trust reasons: disposition-based trust, institution-based trust, presumption-based trust, and interaction-based trust, to examine situational factors in AI-LRS. Our findings reveal that borrowers' trust is influenced not only by their direct interactions with AI-LRS but also by external factors such as social networks and personal traits. We identify the antecedents of trust for the two trust targets: loan scheme quality, reputation of lending institution, structural assurance, social influence, and trust propensity. This contributes to the literature on trust in AI-enabled financial recommendation services and responds to calls for research on trust formation in various decision-support technologies (Wang & Benbasat, 2008). For example, while structural assurance and social influence are generally considered to enhance trust in recommendation services (Kim & Benbasat, 2009), our findings suggest that these factors primarily enhance borrowers' trust in AI-LRS platform. We also apply the ELM as a theoretical framework to understand how borrowers process information. By combining the four trust reasons with ELM, we uncover the mediating role of trust in AI-LRS platform and trust in loan scheme in the relationship between central and peripheral routes and adoption intention. We categorize trust antecedents as either central or peripheral factors and develop a trust framework within a multi-participant environment. This framework clarifies the critical pathways of trust formation and highlights the distinct cognitive processes borrowers use to evaluate different trust antecedents.

Finally, this study extends the contextual boundaries of research on AI trust and decision adoption by examining how repayment pressure moderates the relationship between borrowers' trust and their intention to adopt loan scheme. Previous studies have primarily focused on the direct effects of trust on behavioral intentions (Hsiao et al., 2010; Jin et al., 2021). However, the contextual boundaries that influence trust dynamics remain underexplored. Scholars have called for further research on the variables that shape individuals' perceptions and decisions regarding AI recommendation services (Chua et al., 2023; Shi et al., 2021). Characterized by high threat and cognitive load, repayment pressure aligns with the core concepts of PMT. By integrating PMT with trust research frameworks, this study uncovers the cognitive and behavioral biases borrowers may exhibit under high repayment pressure. Specifically, repayment pressure makes borrowers more cautious in their decision-making. The relationship between trust in the loan scheme and adoption intention weakens, while the relationship between trust in the AI-LRS platform and adoption intention strengthens. Introducing repayment pressure as a moderating variable highlights the complexity of trust in high-stress financial decision-making contexts. Future research could further investigate the moderating effects of other situational variables, such as the urgency of borrowing needs or loan terms, on the relationship between trust and adoption intentions.

7.2. Practical Implications

This research offers several implications for AI-LRS platforms and lending institutions. First, it highlights the importance of trust in encouraging borrowers to adopt recommended loan schemes. Since AI-LRS involves platforms, borrowers, and lending institutions, collaboration between platforms and institutions is essential for establishing and maintaining trust. High-quality loan schemes are crucial in building trust. Platforms should leverage advanced AI technologies to provide accurate and dynamic loan recommendations to meet borrowers' needs. For example, if a borrower's financial situation improves, the AI-LRS platform could proactively suggest more favorable loan schemes, such as lower interest rates or extended repayment periods. Conversely, if risk factors increase, the platform might recommend more conservative loan options or advise financial advisory services, thus improving borrower retention. Meanwhile, lending institutions should have a deep understanding of their loan products to effectively collaborate with platforms, ensuring that the recommended loan schemes align with borrowers' needs. Both platforms and lending institutions should actively seek feedback from borrowers to enhance the effectiveness of AI-LRS. For example, platforms could introduce a rating system that allows borrowers to evaluate recommended loan schemes. To further improve recommendation quality, both platforms and lending institutions could present loan details in various formats, including texts, images, and videos.

Second, AI-LRS platforms should emphasize providing assurance and implementing robust protective measures. These measures might include eliminating commission fees, employing multi-factor authentication to enhance account security, and ensuring privacy throughout the process. Regulatory support is also crucial in strengthening the credibility of AI-LRS platforms. Platforms should proactively collaborate with regulators to create policy frameworks that enhance their legitimacy and build trust among borrowers. Furthermore, given the significant influence of the lending institution's reputation, platforms should establish strict filtering processes to ensure the quality of their partners. For instance, AI-LRS platforms could assign a dynamic reputation score to potential lending partners, prioritizing those with lending institutions that demonstrate responsible lending practices while filtering out those with high-risk or non-compliant behavior. Lending institutions should also recognize the importance of reputation management and foster positive public perceptions through consistent and reliable operations.

Third, social influence plays an important role in fostering borrower trust. AI-LRS platforms could integrate borrowers' social networks into the recommendation process. For example, platforms could anonymously display aggregated data on loan adoption among borrowers' friends or peers. When borrowers see that others in their social network have engaged with recommended loan schemes, they may feel more confident and are more likely to adopt the recommendations.

Fourth, platforms should adapt their recommendation strategies to individual borrower characteristics. With borrowers' consent, platforms could conduct brief surveys to assess factors such as privacy concerns, trust propensity, and tolerance for financial pressure. This data could be used to personalize recommendation strategies. For example, platforms might emphasize low interest rates and favorable loan terms for borrowers experiencing high repayment pressure. To alleviate psychological concerns, they could provide credible information, such as ensuring that recommendations are generated by professional algorithms. For borrowers with high privacy concerns, platforms could increase the frequency of privacy assurance statements. Similarly, for those with low trust propensity in AI, platforms could offer diverse recommendation cues, such as manual reviews or expert suggestions, to build trust and encourage adoption.

7.3. Limitations and Future Research

While this study provides valuable contributions, it also has limitations that offer opportunities for future research. First, we measured adoption intention using self-reported data rather than actual behavior. Although respondents were encouraged to provide realistic answers, the findings may still have limitations, as trust-related factors could influence real borrowing decisions differently. Future research could collect data on actual adoption behavior in real-world AI-LRS environments to validate these findings and provide deeper implications. Second, future studies could explore alternative factors that influence trust and adoption intention from different perspectives. For example, transparency and interactivity are often emphasized in human-AI interactions. Researchers could examine other key technological features in AI-LRS and evaluate their impact on trust and behavioral outcomes. Additionally, the measurement of repayment pressure requires further investigation, as it is a novel variable. Future research could employ multiple methods, such as experiments or interviews, to improve construct validity and enhance the robustness of findings. Finally, this study focused on a fixed loan scheme in its survey design. To better capture real-world borrowing decisions, future research could broaden the scope by using multi-method studies or experimental designs that vary the characteristics of the three key participants.

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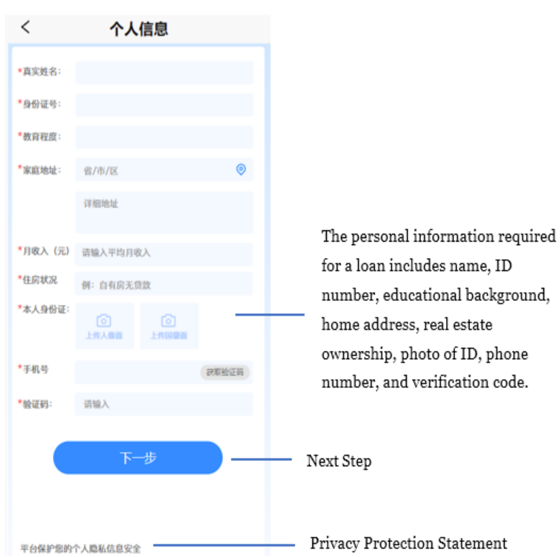
APPENDIX

Appendix 1. Research Scenario

We designed platform prototype diagrams to illustrate the survey scenario. The scenario describes a loan recommendation platform that uses advanced AI technology to provide loan scheme matching services. Specifically, the platform utilizes borrowers' requirements, preferences, credit records, and information from various other sources to accurately recommend the most suitable loan schemes for them. Respondents were asked to imagine themselves as borrowers in need of a 50,000 CNY loan, with access to such an AI-enabled loan recommendation platform for personalized loan schemes. The images below illustrate the platform's operational procedure and key functions. They are for display purposes only and do not require any input from respondents.

(a)

(b)



(c)

(d)

Appendix 2. Questionnaire Items for the Constructs

Loan Scheme Quality (Tseng & Wang, 2016)	
LSQ1	The information presented in the recommended loan scheme is accurate
LSQ2	The information presented in the recommended loan scheme is relevant
LSQ3	The information presented in the recommended loan scheme is comprehensive and complete
Reputation of Lending Institution (Zhou, 2012)	
RLI1	Lending institutions that provide loans are well-known
RLI2	Lending institutions that provide loans have a good reputation
RLI3	Lending institutions that provide loans are known for their honesty
Structural Assurance (Kim & Benbasat, 2009; Shao et al., 2022)	
SA1	The loan recommendation platform has a sufficient number of rules and policy statements
SA2	I feel confident that the loan recommendation platform provides effective policy guarantees
SA3	Overall, the loan recommendation platform provides protective rules and policy guarantees
Social Influence (Wu & Chen, 2017)	
SI1	Other participants' beliefs about the loan recommendation platform encourage me to use it
SI2	Other participants' beliefs about the loan recommendation platform influence my usage of it
SI3	Other participants' beliefs about the loan recommendation platform condition me to use it
Trust Propensity (Gefen, 2000)	
TP1	I usually trust the AI recommendation technique unless I have a reason not to
TP2	I believe that the AI recommendation technique is generally reliable
TP3	I generally trust the AI recommendation technique
TP4	I generally have faith in the AI recommendation technique
Trust in AI-LRS Platform (Bansal et al., 2015; Chen et al., 2018)	
TALP1	The loan recommendation platform is generally trustworthy
TALP2	I have confidence in the reliability of the loan recommendation platform
TALP3	I trust that the loan recommendation platform provides good service
Trust in Loan Scheme (Gefen, 2000; Hsiao et al., 2010)	
TLS1	I believe that the recommended loan schemes are reliable
TLS2	I trust the recommended loan schemes
TLS3	I have confidence in the trustworthiness of the recommended loan schemes
Intention to Adopt Loan Scheme (Teo & Yu, 2005)	
IALS1	I am willing to adopt the recommended loan scheme on the loan recommendation platform
IALS2	I would consider adopting the recommended loan scheme on the loan recommendation platform
IALS3	I am likely to adopt the recommended loan scheme on the loan recommendation platform
Privacy Concern (Dinev & Hart, 2006)	
PC1	I am cautious about sharing my information with loan recommendation platforms or lending institutions due to concerns about how it might be used by others
PC2	I am worried that individuals could access my private information through loan recommendation platforms or lending institutions
PC3	I fear that the information I provide to the loan recommendation platforms or lending institutions could be misused
PC4	I have concerns about sharing my information with loan recommendation platforms or lending institutions, as they could potentially use it in unforeseen ways
Repayment Pressure (Self-developed items)	
RP1	I find it difficult to repay according to the interest rate and date provided in the recommended loan scheme
RP2	I feel pressured to repay according to the interest rate and date provided in the recommended loan scheme
RP3	Repaying according to the interest rate and date specified in the recommended loan scheme is a challenging task for me

RP4	I am concerned that I won’t be able to repay according to the interest rate and date specified in the recommended loan scheme