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Exploring user switching intention to central bank digital currency payments

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ABSTRACT

With the widespread use of mobile devices, mobile payments have become increasingly popular worldwide. In China, third-party providers such as Alipay and WeChat Pay dominate the mobile payment landscape. However, drawbacks of these systems have gradually surfaced, prompting the development of Central Bank Digital Currency (CBDC) payments, most notably China's Digital Yuan (e-CNY). Despite its advantages, CBDC adoption remains limited compared with established third-party platforms. This study investigates the factors influencing users' switching from third-party mobile payments to CBDC payments. Unlike third-party systems, CBDC belongs to the cash category (M0), making it distinct in nature and warranting a tailored research framework. To capture this complexity, the Push-Pull-Mooring (PPM) model was employed, integrated with privacy calculus theory, status quo bias theory, and national identity theory, to construct a comprehensive model of switching intention. Methodologically, a combined approach of partial least squares (PLS), artificial neural networks (ANN), and fuzzy-set qualitative comparative analysis (fsQCA) was adopted. This hybrid strategy enhances robustness and provides nuanced insights into the interplay of causal factors. The findings reveal that privacy concern and trust act as key drivers of users' intention to switch to CBDC payments, whereas inertia represents a significant barrier. These results enrich theoretical research on CBDC payments and extend the application of the PPM model in a novel financial context. Practically, the study informs policymakers and managers by highlighting the importance of targeted strategies that strengthen trust, address privacy issues, and reduce switching barriers, thereby accelerating CBDC adoption.

Contribution/Originality: This study develops a tailored PPM-based framework by integrating privacy concerns, inertia, and trust to explain user switching to CBDC payments, enriches theoretical understanding through a novel PLS-ANN-fsQCA approach, and offers targeted policy insights that help governments and central banks strengthen e-CNY adoption, user confidence, and financial inclusion.

1. INTRODUCTION

With the continuous advancement of mobile communication technology, mobile payment has become the mainstream method of modern transactions, replacing traditional cash and credit card payments. Mobile payment enables contactless payment through portable devices, which not only revolutionizes consumers' payment habits but also promotes the development of the digital economy (Patil, Tamilmani, Rana, & Raghavan, 2020). In recent years, mobile payment technology has developed rapidly, and a variety of payment methods have emerged, such as SMS payment, QR code payment, NFC payment, and biometric payment, which are provided by financial institutions and innovative companies such as Apple Pay, Google Pay, and Alipay (Leong, Tan, Xiao, Tan, & Sun, 2017). Mobile payment has a significantly higher adoption rate worldwide, especially in Asian countries such as China and Japan, than in Europe and North America (Boden, Maier, & Wilken, 2020; Shin & Lee, 2021). However, mobile payment also faces security issues such as privacy leakage (Park, Amendah, Lee, & Hyun, 2019). During the COVID-19 epidemic, the importance of mobile payment has become more prominent, helping to implement social isolation policies and promote online services (Al-Sharafi, Al-Qaysi, Iahad, & Al-Emran, 2022).

China is a global leader in mobile payments and digital wallet services, with Alipay and WeChat Pay dominating the market. The digital yuan (e-CNY), launched by the People's Bank of China as an officially recognized central bank digital currency (CBDC), is currently in the active stage of pilot expansion and is expected to accelerate the reduction of physical cash use. As the most advanced stage of digital currency development, CBDC carries the backing of national credit and holds legal tender status. In recent years, it has become a focal point of academic and policy discourse (Adrian & Mancini-Griffoli, 2019). The global development of CBDCs is progressing steadily, with many central banks accelerating research and implementation (Yao, 2020).

Although CBDC has attracted substantial scholarly and policy attention, existing studies primarily examine its macro-level implications, such as monetary policy effectiveness, financial stability, and broader economic impact. These studies have provided valuable insights into the systemic role of CBDC in reshaping financial markets and economies, but they largely neglect the micro-level perspective particularly the behavioral dynamics of individual users who ultimately determine the practical success of CBDC adoption.

By contrast, research on mobile payments has extensively investigated user acceptance and adoption behaviors. However, few studies have systematically explored users' switching intentions from dominant third-party platforms (e.g., Alipay and WeChat Pay) to CBDC-based alternatives such as the e-CNY. Given that individual adoption behavior is a decisive factor for CBDC viability and diffusion, this gap represents an important academic shortcoming. Addressing it is essential not only for advancing theoretical understanding of CBDC adoption but also for providing policymakers and system designers with practical guidance to reduce barriers to user switching.

Although e-CNY shares technical similarities with existing mobile payment methods, its unique status as legal currency necessitates the development of new analytical frameworks (Xia, Gao, & Zhang, 2023). Compared with third-party platforms, CBDC payments demonstrate distinctive advantages. Despite gradual growth in e-CNY use, its market penetration remains limited: Alipay and WeChat Pay account for over 90 percent of China's mobile payment market, whereas e-CNY accounts for less than 10 percent (Shen, Faklaris, Jin, Dabbish, & Hong, 2020). Understanding the factors that influence users to switch from third-party mobile payments to e-CNY has therefore become the central focus of this study.

This research is guided by three questions:

- RQ1: What features of third-party mobile payments drive users to switch to e-CNY payment?
- RQ2: What features of third-party mobile payments hinder users switching to e-CNY payment?
- RQ3: What features of e-CNY payment attract users to switch from third-party mobile payments?

While most studies address the macroeconomic effects of e-CNY (Kshetri, 2023), this study emphasizes the micro-level perspective of users' switching intentions. To address this gap, it applies the push–pull–mooring (PPM) model, examining how the disadvantages of third-party platforms (push), individual user factors (mooring), and the advantages of CBDC payments (pull) influence switching behavior.

The remainder of this paper is structured as follows. Section 1 introduces the research background. Section 2 reviews relevant literature on mobile payments and CBDCs. Section 3 develops the research variables and hypotheses. Section 4 outlines the research methodology. Section 5 presents the data analysis, applying the three-stage method of PLS-ANN-fsQCA. Section 6 discusses the findings and offers policy recommendations. Finally, Section 7 highlights the study's contributions, significance, and limitations.

2. LITERATURE REVIEW

2.1. Mobile Payments

Mobile payment refers to the transfer of monetary value through mobile devices to settle claims and debts. It can be defined in both narrow and broad terms: in the narrow sense, it refers specifically to mobile phone payments, while in the broader sense, it encompasses payments made via other mobile communication devices as well (Loh, Lee, Tan, Ooi, & Dwivedi, 2021). Existing research on mobile payment primarily focuses on three dimensions: the mobile payment ecosystem, mobile payment technology, and user adoption.

In terms of ecosystem research, Pousttchi, Schiessler, and Wiedemann (2009) proposed a mobile payment business model framework that highlighted challenges in customer acceptance and service provider recognition. More recently, Lee, Chen, and Chu (2023) examined the role of mobile payment in promoting financial inclusion and environmental sustainability. From a technological perspective, Shaghayegh (2011) emphasized the role of smartphones as digital wallets and suggested employing service-oriented architecture in system design. Obaid, Bayram, and Saleh (2019) introduced a communication network model aimed at directly connecting banks with customers, while Sanni, Akinyemi, Olalere, Olajubu, and Aderounmu (2023) explored the development of mobile money services and their opportunities and challenges for inclusive finance in developing countries.

Studies on user adoption form the largest body of mobile payment research. Al Amin, Muzareba, Chowdhury, and Khondkar (2023) investigated multidimensional factors influencing e-satisfaction, continued use intention, and e-loyalty. Tew et al. (2022) applied the MTAM framework to identify determinants of near-field communication (NFC) payment adoption. De Luna, Liébana-Cabanillas, Sánchez-Fernández, and Muñoz-Leiva (2019) and Quan, Moon, Kim, and Han (2023) examined user attitudes toward different mobile payment systems, while Patil et al. (2020) and Migliore, Wagner, Cechella, and Liébana-Cabanillas (2022) explored adoption behaviors in developing countries. Much of this research has been grounded in models such as TAM and UTAUT, which consistently identify perceived usefulness, ease of use, and trust as critical drivers of adoption (Patil et al., 2020; Tew et al., 2022). While these approaches provide valuable insights, they primarily address initial adoption and give limited attention to the role of established systems in shaping user behavior.

Recent studies highlight that entrenched habits, switching costs, and perceived risks strongly influence whether users abandon established platforms (Loh et al., 2021; Quan et al., 2023). This suggests that adoption research focused solely on "new" technology is incomplete, as ties to existing technologies significantly affect decision-making. Thus, frameworks that capture both old and new technology characteristics such as the push–pull–mooring (PPM) model are more suitable for analyzing switching behavior.

A review of the literature reveals two main research gaps. First, while most studies emphasize the adoption of new technologies, they overlook the importance of old technology characteristics in shaping user conversion. The TAM and UTAUT models, therefore, provide only a partial explanation, as they do not account for the influence of legacy systems. The PPM model, widely applied in switching behavior research, (Hsieh, 2021; Nayak, Bhattacharyya, Kulkarni, & Mehdi, 2023; Wang, Wong, Liu, & Yuen, 2021) addresses this limitation by simultaneously considering the disadvantages of old technologies (push factors) and the advantages of new technologies (pull factors), alongside personal and contextual influences (mooring factors).

Second, although user adoption of mainstream mobile payment systems has been well studied, less attention has been given to the relationship between dominant platforms and emerging payment technologies, such as central bank digital currencies (CBDCs). The COVID-19 pandemic accelerated global interest in CBDCs as governments promoted contactless payment solutions. However, few studies have applied the PPM model to analyze CBDC adoption. By focusing on user switching from third-party mobile payments to CBDC-based payments, this study aims to fill this gap.

2.2. Central Bank Digital Currency

Central bank digital currency (CBDC) is a form of digital money issued by central banks, supported by technologies such as blockchain and artificial intelligence. It possesses the essential attributes of modern credit currency, is backed by national credit, and has legal tender status. Unlike traditional bank-based systems, CBDC can facilitate payments and transfers without relying on commercial bank accounts (Auer, Cornelli, & Frost, 2020). In recent years, CBDC has attracted significant attention as a major innovation in financial technology.

Scholars have extensively examined its optimal design and macroeconomic implications. Barrdear and Kumhof (2022) using a DSGE model, found that CBDC issuance could permanently raise GDP by 3% and enhance central banks' ability to stabilize economic cycles. Davoodalhosseini (2022) argued that CBDC use could improve resource allocation efficiency, though the coexistence of cash and CBDC might reduce welfare. In terms of financial markets, Wang et al. (2021) constructed a CBDC uncertainty index and an attention index, finding that markets react sensitively to CBDC uncertainty. Li, Yang, and Huang (2022) examined the feedback effects of CBDC-related signals in the fintech sector and noted that the intensity of market responses diminishes over time.

A review of existing studies reveals that research on CBDC payments remains limited in scope and primarily macro-focused. Most work emphasizes the economic value of CBDCs and their systemic impact, while micro-level perspectives particularly user adoption behavior remain underexplored. This study seeks to address this gap by investigating the behavioral dynamics of CBDC adoption. Specifically, we apply the push–pull–mooring (PPM) model to analyze switching behavior between third-party mobile payments and CBDC payments. The PPM framework explains users' willingness to adopt new technologies by simultaneously considering the disadvantages of existing systems (push factors) and the advantages of new alternatives (pull factors), moderated by personal and contextual influences (mooring factors). This dual-perspective approach provides a comprehensive lens for examining switching intentions.

Although the literature on CBDC is expanding rapidly, its emphasis remains on macro-level issues such as monetary policy, financial stability, and systemic innovation (Barrdear & Kumhof, 2022; Wang et al., 2021). While these studies underscore the transformative potential of CBDC, they largely overlook how individual-level behaviors may facilitate or hinder adoption. At the micro level, only limited research has investigated user acceptance and switching intentions toward CBDC (Wu, An, Wang, & Shin, 2022). Given that widespread adoption ultimately depends on end-users rather than macroeconomic design, this gap is both significant and pressing. By shifting attention from systemic outcomes to user-level behavioral dynamics, this study contributes to a more complete understanding of CBDC adoption.

2.3. Push-Pull-Mooring Model

This study adopts the Push–Pull–Mooring (PPM) model as its research framework. Initially developed to explain patterns of cultural and geographical migration (Nayak et al., 2023), the PPM model has since been extended to a wide range of contexts, particularly in analyzing technology adoption and service-switching behavior (Hsieh, 2021). The model is built on three key components push, pull, and mooring factors (Nayak et al., 2023). Push factors capture the drivers that push individuals away from their current state; pull factors represent the attractions of alternative options; and mooring factors reflect personal or contextual conditions that may either facilitate or hinder switching (Yusfiarto, Sunarsih, & Darmawan, 2023). Importantly, the composition and influence of these factors vary across migration types and research domains.

With the rapid advancement of digital technologies, switching behavior has become an important focus in contemporary scholarship. Numerous studies have demonstrated the explanatory strength of the PPM model in this area (Handarkho & Harjoseputro, 2020; Lin, Jin, Zhao, Yu, & Su, 2021). For example, Lin et al. (2021) found that security concerns (push), pedagogical utility (pull), and switching costs or habitual routines (mooring) collectively shaped educators' willingness to transition to online teaching. Similarly, Handarkho and Harjoseputro (2020) showed that consumer innovativeness, transaction propensity, ease of use, and herding behavior influenced the adoption of mobile payments, with enjoyment and subjective norms exerting indirect effects through perceived ease of use.

The PPM model has proven valuable in explaining technology-switching decisions by integrating dissatisfaction with existing systems (push), attraction to alternatives (pull), and individual or contextual constraints (mooring) Lin et al., 2021; Nayak et al., 2023). Unlike models such as TAM or UTAUT, which focus primarily on adoption drivers, PPM offers a more holistic perspective by addressing both the motivations to adopt and the reasons users remain with incumbent systems. Despite its strengths, applications of PPM in the context of central bank digital currencies (CBDCs) remain scarce. By employing this framework, the present study extends PPM research into a new domain and provides a more comprehensive understanding of user switching from dominant third-party mobile payment platforms to e-CNY.

3. HYPOTHETICAL DEVELOPMENT

3.1. Privacy Concern

Privacy concern is commonly defined as the extent to which individuals are worried about the protection of their personal information (Lenz, Bozakov, Wendzel, & Vrhovec, 2023). Drawing on Lenz et al. (2023), this study distinguishes privacy concern into two dimensions: concerns related to data collection and concerns related to improper access. The former refers to users' unease regarding the collection of personal information by established mobile payment providers such as Alipay, while the latter reflects apprehensions about unauthorized access to and misuse of information already collected and stored by service operators.

The relationship between privacy concerns and users' willingness to switch technologies has been widely examined across domains. Lenz et al. (2023) observed that while the perceived utility of new devices influences replacement intention, it is less strongly tied to other adoption factors; instead, privacy risks associated with existing technologies and the costs of switching play a significant role in decision-making. In the social media context, Jozani, Ayaburi, Ko, and Choo (2020) found that both institutional and social privacy concerns reduce user engagement. They showed that sensitivity of information heightens institutional concerns, while social privacy issues are shaped by users' perceptions of risk and control. Similarly, Xia et al. (2023), integrating the PPM framework with Task-Technology Fit (TTF) theory, revealed that concerns around privacy and technical-task compatibility negatively influence the adoption of digital currency electronic payment (DCEP) and increase switching costs. Research in other digital contexts also highlights the pivotal role of privacy. For instance, Vimalkumar, Sharma, Singh, and Dwivedi (2021) demonstrated that in the adoption of voice-based digital assistants (VBDA), perceived privacy risks are not only shaped by privacy concerns themselves but are also moderated by trust, which emerges as a critical determinant of use.

Privacy calculus theory explains the relationship of the push factor variable (privacy concern) in this research model. The theory was proposed by Laufer and Wolfe (1977) pointing out that users will weigh privacy risks and benefits when using third-party mobile payment applications. When privacy risks outweigh benefits, users may consider switching payment methods. In the digital environment, consumers recognize the potential risks of disclosing personal information; hence, they generally conduct risk-benefit assessments to decide whether to authorize companies to obtain private information. Privacy calculus theory is based on rational choice and aims to maximize expected positive results and minimize expected negative results (Vroom, 1964), which is closely linked to the expected utility hypothesis in game theory. When predicting results, individuals consider the probability and impact of positive and negative events (Friedman & Savage, 1952) to make behavioral choices. Based on the above literature summary, this paper believes that users' privacy concerns about third-party mobile payments are closely related to their intention to switch to using e-CNY payment. First, the operators of third-party mobile payment applications are mostly private enterprises, including Alipay and WeChat Pay. The security level of the databases they use to store user data is not at the same level as the security level of the central bank's database. The security level of the central bank's database for storing user data is higher (Lee, Son, Park, Lee, & Jang, 2021). Therefore, compared with the e-CNY, users of third-party payment applications may worry about illegal access to personal data in the database. Users' privacy concerns about illegal access to personal data may lead users to consider switching to other mobile payment methods. Secondly, since third-party mobile payment applications are mainly profit-oriented, they often add additional functions beyond payment to the program. These functions require the application to collect more user personal information. In contrast, the central bank digital currency payment application is a non-profit program, and its functions are primarily focused on payment services. Therefore, users of third-party payment applications may be more concerned about the collection of personal data, which could influence their decision to use alternative mobile payment tools. Consequently, this paper proposes the following hypothesis:

H_1: Privacy concerns have a significantly positive relationship with switching intention.

3.2. Payment Habit

Payment habits are defined as mobile payment methods that people often use in their daily lives (Loh et al., 2021). In recent years, the academic community has shown a significant growth trend in exploring the complex relationship between users' payment habits and their payment behaviors. These studies have deeply revealed the impact mechanisms of payment habits on payment behaviors from multiple dimensions. The research of Loh et al. (2021) first pointed out that payment habits are the key factor driving the formation of users' payment behavior inertia, providing a solid theoretical basis for understanding payment behavior and emphasizing the core role of habits in the payment decision-making process.

Accordingly, Loh et al. (2021) analyzed reluctance towards acceptance of payment with cryptocurrencies in a sharing economy scenario. Building on the theory of status quo bias, a theoretical model and an empirical analysis were developed, utilizing a mixed-methods approach that included an online survey and SEM-fsQCA analysis. The results indicated that perceived complexity, skepticism, existing payment habits, and behavioral inertia are key factors contributing to resistance attitudes. These findings underscore the numerous challenges faced by new technologies within the sharing economy and highlight the significant influence of users' established habits on the acceptance of innovative payment methods. In particular, in the Chinese market, where Alipay and WeChat Pay have been deeply integrated for many years, users have developed entrenched usage habits, which are likely to produce an inertial effect on payment behavior. Based on this detailed analysis, the paper proposes several hypotheses for further empirical testing.

H_2: Payment habits have a significantly positive relationship with inertia.

3.3. Switching Cost

Switching cost is defined as the cost that users pay for switching from old technology to new technology, including learning costs, time costs, among others (Loh et al., 2021). In this paper, it mainly refers to the cost of switching from using Alipay and WeChat Pay to e-CNY payments. In recent years, switching cost, as a core factor affecting user behavior inertia and the degree of acceptance of new technologies, has attracted widespread attention in the academic community. Many studies have researched in detail the mechanism of switching costs from numerous dimensions. Loh et al. (2021) clearly demonstrated that switching costs are a significant barrier to mobile payment acceptance among users. This finding confirms that switching costs play a role in the decision-making process involved in user behavior. Similarly, Hsieh (2021) found in his study of medical mobile payment (MMP) application usage that use behavior, switching cost, and sunk cost all have a detrimental impact on willingness to switch, and confirm that switching cost is involved in maintaining user behavior inertia. In a survey researching users' attitudes towards new technology resistance, Balakrishnan, Dwivedi, Hughes, and Boy (2024) found that even when inertia did not have a significant relation with artificial intelligence voice assistants (AIVA) resistance, perceived value exhibited a negative relation with attitude towards resistance, and inertia between groups with different genders and age groups exhibited variation. It opens a new perspective for explaining new technology acceptance among users.

Shankar and Nigam (2022), in terms of status quo bias theory, attested that inertia, regret aversion, switching costs, and perceived danger have a significant impact on HR professionals' disposition towards rejecting cloud-based mHRM software. Not only did this research enrich the theoretical understanding of switching costs, but it also emphasized the significant role of individual innovation. Additionally, the research by Cao, Yao, and Chen (2020) and Dogra, Bakshi, and Gupta (2023) further expanded the application scope of switching costs. Cao et al. (2020) found that emotional commitment, switching costs, and habits together constituted an important basis for users to switch from blog platforms to Weibo platforms. Although switching costs have been examined in areas such as e-health and mobile services (Dogra et al., 2023), their relevance to CBDC adoption remains underexplored. Given that e-CNY is still unfamiliar to many users, the perceived effort of learning and integration is likely to exacerbate inertia. Therefore, switching costs may become an important factor leading to user inertia. Based on this, this paper proposes the following hypothesis to be verified.

H_3: Switching cost has a significantly positive relationship with inertia.

3.4. Inertia

Inertia is a tendency where individuals tend to maintain the use of existing systems despite the availability of superior alternatives (Polites & Karahanna, 2012). Polites and Karahanna (2012) defined inertia from three dimensions: behavior, cognition, and emotion. Specifically, behavioral inertia describes a propensity for current use and continued use of the current system, while cognitive inertia refers to a state in which, even when a user is aware of a preferable alternative, they deliberately maintain their current use decision. Emotional inertia describes a state where a user continues using the current system due to psychological burdens associated with switching or strong feelings of affiliation with the current working practice (Hsieh, 2021).

Prior research shows that inertia is a significant barrier to switching in digital payments (Gong, Zhang, Chen, Cheung, & Lee, 2020; Kuo, 2020). Little research has examined how inertia interacts with CBDC adoption, where trust in a government-backed system could counterbalance entrenched habits. This study contributes by analyzing inertia's direct effect on switching intention in the CBDC context. Kuo (2020) applied the push-pull-mooring framework to demonstrate that regret and the attractiveness of alternatives are positively correlated with users' willingness to switch, whereas inertia is negatively correlated with the intention to switch. The Status Quo Bias (SQB) theory explains the relationships between variables such as payment habits, switching costs, and inertia within this research model. According to SQB theory, users' habits with third-party mobile payments and the switching costs associated with transitioning to e-CNY payments contribute to their inertia. The theory further explores the decision-making psychology of individuals who tend to stick with existing behaviors or systems when faced with new or better options. It posits that individuals naturally consider the status quo during decision-making, which often becomes a barrier to adopting alternatives, thereby influencing their final choice (Wu, 2016). This phenomenon is attributed to inertia, which is shaped by factors like relational decision-making, psychological attachment, and cognitive bias (Zhang, Guo, Wu, Lai, & Vogel, 2017). When switching to e-CNY payment, users' strong behavioural inertia may lead them to prefer existing third-party payment systems. Behavioural inertia refers to continued use due to habit; cognitive inertia refers to continued use despite awareness of non-optimal alternatives; and affective inertia refers to continued use due to switching pressure or emotional attachment to the current method. Based on this, the paper proposes the following hypothesis:

H_4: Inertia has a significantly negative relationship with switching intention.

3.5. Trust

In mobile payment user acceptance behavior, the concept of trust is generally understood as an initial sense of trust that users develop when they first contact and adopt mobile payment services. This trust is constructed by the joint action of many facilitating and hindering forces and has an important impact on the initial use intention and follow-up continuous use intention of users. Initial trust is the trust state when users have their first experience with mobile payment services. As the emotional feedback of the user's first interaction, this state has a significant impact on the user's engagement with the subsequent transaction process (Cao, Yu, Liu, Gong, & Adeel, 2018; Talwar, Dhir, Khalil, Mohan, & Islam, 2020). Moreover, initial trust is considered a significant driver of innovation acceptance, which has a direct influence on users' confirmation, perceived usefulness, and intention to continue using (Gao et al., 2015). Specifically, trust was verified as a bridge mechanism linking transaction satisfaction and repurchase intention within research on Airbnb (Liang, Choi, & Joppe, 2018). Trust directly influences the usage of the system by users, while increasing users' social capital with the system and its users leads to a transition to migration intention indirectly. This social capital represents a switching cost for viewers, one that reinforces the incentive to maintain use (Turel & Gefen, 2013). In the case of service failure, an inverted U-shaped relationship was found between customers' expected trust in providers and their intention to switch brands. Rational trust at a moderate level reduces the likelihood of customers switching services because they will tolerate service failures (Cui, Zhang, & Zhong, 2023). Regarding social network platforms research, users tend to weigh the estimated value and potential risks of the new platform, carefully consider whether to switch, and subsequently build trust in the new environment. These factors influence users' switching intentions (Lin & Wang, 2017).

Users' trust in e-CNY payment will have a positive effect on their switching intention. Specifically, when users have established a deep foundation of trust in the e-CNY payment system, they will be more inclined to adopt this new payment method and consider it as the main or an alternative payment method. This trust stems from the recognition of the security, convenience, and stability of e-CNY payment. It can not only enhance users' confidence in use but also inspire users' willingness to try and accept new payment methods. Therefore, as users' trust in e-CNY payment continues to increase, their intention to switch to e-CNY payment will also increase. This paper proposes the following hypothesis:

H_5: Trust has a significantly positive relationship with switching intention.

3.6. National Identity

National identity refers to an individual's sense of belonging and identification with their country. Prior research shows that national identity significantly shapes consumer behavior across domains, ranging from product consumption (Jia et al., 2023; Sun, Gonzalez-Jimenez, & Wang, 2021) to the adoption of digital currencies (Wu et al., 2022). For instance, Jia et al. (2023) emphasize the role of social norms and national identity in fostering Chinese consumers' preference for domestic products, noting its particularly strong influence among younger cohorts. Sun et al. (2021) further reveal that ethnocentrism, closely tied to national identity, affects brand equity depending on the origin of brand information. In the digital currency context, Wu et al. (2022) found that fairness perceptions, habitual use, social influence, and national identity jointly influence the adoption of central bank digital currency electronic payment (DCEP), with national identity also acting as a significant moderator of these relationships.

In this study, national identity is conceptualized as a pull factor within the research framework, explaining its role in shaping switching intentions toward e-CNY. National identity theory suggests that users who identify strongly with the Chinese nation are more inclined to adopt the central bank's digital payment system. Consumers often express national consciousness in the marketplace, signaling their sense of belonging by favoring products with domestic origins over foreign alternatives. In a globalized environment where identity construction is increasingly complex, national identity serves as a vital reference system that enables individuals to situate themselves and affirm self-identity. Accordingly, given that e-CNY represents a sovereign digital payment system backed by the People's

Bank of China, its strong national symbolism is likely to appeal to users with heightened national identity, thereby increasing their intention to switch from third-party mobile payments to e-CNY. Therefore, this paper proposes the following hypothesis:

H_6: National identity has a significantly positive relationship with switching intention.

Based on the above hypothesis, the research model of this study was proposed (see Figure 1).

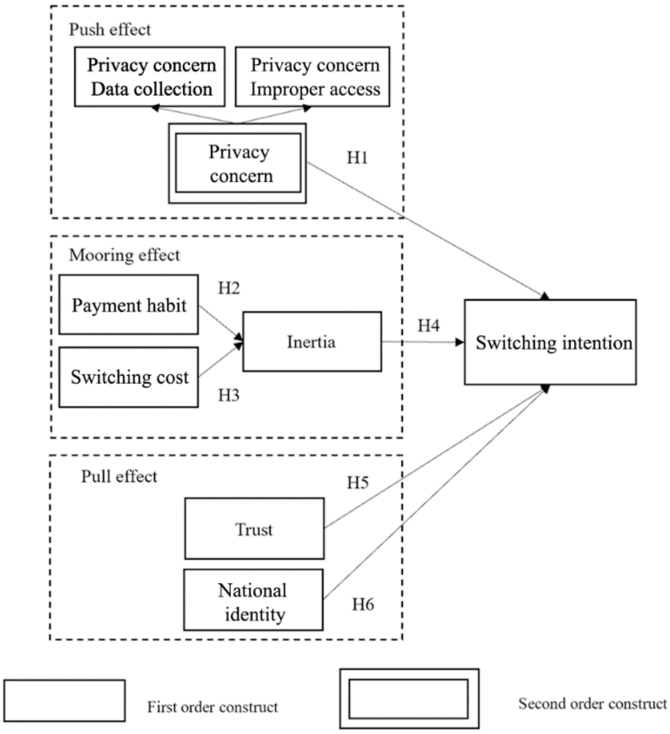


Figure 1. Research model.

4. RESEARCH METHODS

Given the absence of a well-defined sampling frame, this study employed a convenience sampling strategy to flexibly recruit respondents. While this approach facilitated accessibility and ensured sufficient participation, its non-probability nature inevitably constrains sample representativeness and the generalizability of findings. To address these limitations, future research could consider adopting stratified or random sampling techniques to strengthen external validity. Data were collected through a self-administered online questionnaire survey, a method widely applied in technology acceptance research and particularly suited for examining users' switching intentions toward CBDC payments. The questionnaire items were adapted from established measurement scales in prior studies (see Table 1) and assessed using a seven-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7). Distribution was carried out via the "Wen Juan Xing" platform, which hosts over three million registered users, thereby enhancing geographic diversity and partly compensating for the limitations of convenience sampling (Li et al., 2020). To ensure content validity and linguistic accuracy, four independent experts in technology acceptance research reviewed the questionnaire indicators. Revisions were made to improve layout and clarity, and the instrument was translated into Chinese through a rigorous forward–backward translation procedure. A pilot test was conducted prior to large-scale distribution to further validate the reliability and applicability of the instrument. During the formal data collection phase, 360 valid responses were obtained. This sample size substantially exceeded the minimum requirement of 85 participants, as calculated using G*Power software under the parameters of statistical power (0.80), significance level (0.05), expected effect size (0.15), and four predictor variables. The final sample thus provides a robust basis for subsequent statistical analyses.

Table 1. Measurement items.

Construct	Items	Sources
Privacy concern – data collection	It bothers me that Alipay and WeChat Pay collect my personal information. I reconsider my choices when these apps request personal information. I am concerned that Alipay and WeChat Pay collect too much personal information about me. I worry about the extent to which these apps are designed to collect personal data.	Adapted from Lenz et al. (2023)
Privacy concern – improper access	I am concerned that the databases of Alipay and WeChat Pay are vulnerable to unauthorized access. I am concerned that these providers do not devote sufficient effort to preventing unauthorized access. I am concerned that they do not take adequate steps to ensure that unauthorized persons cannot access my information.	Adapted from Lenz et al. (2023)
Payment habit	Whenever I need to pay, I automatically use Alipay or WeChat Pay. I tend to choose Alipay or WeChat Pay without consciously considering alternatives. It would be difficult to control my tendency to use these apps when paying. I do not need to expend much mental effort when deciding to use Alipay or WeChat Pay.	Adapted from Loh et al. (2021)
Switching cost	Learning how to use e-CNY payment would take time. Registering and becoming familiar with e-CNY will require effort. Switching from Alipay/WeChat Pay to e-CNY would demand considerable effort. Switching would also take considerable time. Becoming skilled at using e-CNY would not be easy for me.	Adapted from Xia et al. (2023) and Loh et al. (2021)
Behavioural inertia	I continue using the current method because I prefer consistency. I use the current method as it is part of my daily routine. I continue with the current method because it has become a regular habit.	Adopted from Hsieh (2021)
Cognitive inertia	I continue using the current method even though I know it is not the best solution. I continue using it even though I know it is not the most efficient method.	Adopted from Hsieh (2021)
Affective inertia	I continue using the current method because making changes would be stressful. I continue using it because it feels comfortable. I continue using it because I enjoy doing so.	Adopted from Hsieh (2021)
Trust	I believe that e-CNY payment is honest. I believe that e-CNY payment is trustworthy. I believe that e-CNY payment is dependable. I believe that e-CNY payment is reliable.	Adapted from Bawack, Wamba, and Carillo (2021)
National identity	I feel a strong sense of belonging to China. I am proud of China in general. I am proud of China's history and culture. I am proud of China's economic development.	Adopted from C. X. Zhang, Fong, Li, and Ly (2019)
Switching intention	I am considering switching from Alipay/WeChat Pay to e-CNY. The likelihood of my switching to e-CNY is high. I will switch to e-CNY if it satisfies my payment needs. I am determined to switch from Alipay/WeChat Pay to e-CNY. I intend to switch to e-CNY in the future. I am willing to invest time and effort into adopting e-CNY.	Adapted from Loh et al. (2021)

To ensure that participants possessed sufficient familiarity with mobile payment systems, the questionnaire incorporated screening questions. Only individuals who reported using third-party payment platforms as their primary mobile payment method and who had prior experience with or awareness of e-CNY were retained in the sample. Demographic information was collected at the end of the survey (see Table 2), including gender, age, education level, frequency of mobile payment use, and years of mobile payment experience. In terms of gender distribution, females represented 53.33% of the sample, while males accounted for 46.67%. Regarding age composition, the largest group of respondents fell within the 31–40 age bracket, comprising 33.89% of the total. In terms of experience with mobile payments, an overwhelming majority (96.11%) reported using such services for more than three years, indicating strong familiarity with the technology. Concerning usage frequency, nearly half of the respondents (48.33%) indicated that they conducted mobile payments between six and ten times per day, thereby meeting the study's requirement that participants have substantive usage experience. Finally, in terms of educational background, 56.94% of respondents held either a diploma or a bachelor's degree.

Table 2. Demographic profile of respondents.

Demographic variable	Category	Frequency	Percentage (%)
Gender	Male	168	46.67%
	Female	192	53.33%
Age	18-20	7	1.94%
	21-30	85	23.61%
	31-40	122	33.89%
	41-50	105	29.17%
	51-60	32	8.89%
	＞60	9	2.50%
Education	Junior high school and below	23	6.39%
	High school	84	23.33%
	Diploma	133	36.94%
	Bachelor	72	20.00%
	Master and above	48	13.33%
Mobile payment experience	1-2 years	14	3.89%
	3-4 years	71	19.72%
	5-6 years	99	27.50%
	7-8 years	97	26.94%
	9-10 years	62	17.22%
	＞10 years	17	4.72%
Frequency of using mobile payment	1 time a day	11	3.06%
	2-5 times a day	89	24.72%
	6-10 times a day	174	48.33%
	>10 times a day	86	23.89%

5. DATA ANALYSIS

This study employed a composite analytical strategy that integrated three sequential methods: partial least squares-structural equation modelling (PLS-SEM), artificial neural network (ANN) analysis, and fuzzy-set qualitative comparative analysis (fsQCA). Together, this multi-method approach referred to as the PLS-ANN-fsQCA synthesis enabled a comprehensive examination of the dataset from multiple perspectives.

In the first stage, SmartPLS software was used to conduct PLS-SEM analysis to test the hypothesized relationships among variables. PLS-SEM is well established as a robust technique for identifying linear associations in complex models. However, it has two key limitations. First, structural equation modeling (SEM) has limited capacity to capture nonlinear relationships (Leong, Hew, Ooi, Tan, & Koohang, 2025). Second, SEM treats variable relationships in a simplified manner, overlooking the complexity inherent in user behavior (Pappas & Woodside, 2021).

To address these limitations, the second stage introduced ANN analysis, which allows for the detection of nonlinear effects and provides additional validation for the PLS-SEM path model (Leong et al., 2025). ANN operates through a multilayered architecture of input, hidden, and output neurons, simulating human cognitive decision-making and offering a powerful means of exploring nonlinear patterns in data (Chong, 2013). Nevertheless, ANN is not without drawbacks. Its "black box" nature limits interpretability, as the internal logic of its processes is difficult to explain. By combining ANN with the linear predictive strengths of PLS-SEM, this study leverages the complementary advantages of both techniques.

Finally, to overcome the limitations of SEM in addressing the multifaceted and combinatorial nature of causal relationships, fsQCA was incorporated in the third stage. FsQCA is an asymmetric method that identifies both necessary and sufficient conditions for outcomes, capturing how different causal configurations may lead to the same result (Pappas & Woodside, 2021). It provides richer insights into causal complexity than traditional regression approaches, which tend to isolate net effects of single variables. As Fiss (2011) notes, fsQCA enables the identification of multiple pathways to outcomes, thus clarifying the interplay of conditions that drive user intentions.

By integrating PLS-SEM, ANN, and fsQCA, this study adopts a comprehensive and complementary analytical framework. This synthesis not only validates linear relationships but also uncovers nonlinear dynamics and complex causal pathways, thereby offering a deeper and more holistic understanding of the factors influencing user switching behavior.

5.1. Common Method Bias

To address common method bias, this study adopted a dual strategy of procedural control and statistical analysis, focusing on accurate information transmission. The statistical analysis used Harman's single-factor test (Table 3), and the results showed that the total variance explained by the largest single factor was 21.362%, far below the critical value of 50% (Tew et al., 2022), indicating that there was no single factor dominating the data set. The correlation coefficient matrix analysis also showed that the correlation coefficients between variables did not reach 0.9 (Table 4), further confirming that the common method bias was not a significant interference. In summary, the combination of dual paths effectively reduced the impact of common method bias and improved the robustness and credibility of the research analysis.

Table 3. Harman's single-factor test.

Total variance explained						
Component	**Initial eigenvalues**			**Extraction sums of squared loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	8.104	21.326	21.326	8.104	21.326	21.326
2	6.113	16.087	37.413			
3	2.475	6.514	43.927			
4	2.170	5.710	49.637			
5	2.032	5.349	54.986			
6	1.592	4.189	59.175			
7	1.388	3.651	62.826			
8	0.982	2.585	65.411			
9	0.864	2.273	67.684			
10	0.759	1.996	69.680			
11	0.722	1.901	71.581			
12	0.662	1.743	73.324			
13	0.649	1.707	75.031			
14	0.600	1.579	76.610			
15	0.596	1.567	78.178			
16	0.569	1.496	79.674			
17	0.536	1.412	81.086			

Total variance explained						
Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
18	0.516	1.357	82.443			
19	0.500	1.315	83.758			
20	0.482	1.267	85.025			
21	0.461	1.213	86.238			
22	0.437	1.149	87.387			
23	0.405	1.065	88.452			
24	0.394	1.037	89.489			
25	0.373	0.983	90.472			
26	0.368	0.968	91.440			
27	0.351	0.924	92.364			
28	0.340	0.894	93.258			
29	0.328	0.864	94.122			
30	0.315	0.829	94.951			
31	0.300	0.790	95.741			
32	0.289	0.761	96.502			
33	0.268	0.705	97.207			
34	0.253	0.665	97.872			
35	0.225	0.593	98.465			
36	0.221	0.581	99.046			
37	0.203	0.533	99.579			
38	0.160	0.421	100.000			
Extraction Method: Principal Component Analysis.						

Table 4. Correlation matrix

Variables	IN	NI	PCDC	PCIA	PH	SC	SI	T
IN	0.759							
NI	0.018	0.862						
PCDC	-0.068	0.275	0.778					
PCIA	-0.025	0.193	0.556	0.795				
PH	0.540	0.006	-0.160	-0.141	0.855			
SC	0.494	0.011	-0.112	-0.080	0.404	0.836		
SI	-0.179	0.270	0.465	0.431	-0.112	-0.131	0.781	
T	0.000	0.273	0.397	0.388	-0.024	-0.065	0.438	0.778

Note: Inertia (IN); National identity (NI); Privacy concern data collection (PCDC); Privacy concern improper access (PCIA); Payment habit (PH); Switching cost (SC); Switching intention (SI); Trust (T).

5.2. External Measurement Model

This study examines the stability of the external measurement model data, using Cronbach's Alpha coefficient and composite reliability, both far exceeding the minimum standard of 0.7 (Hair, Risher, Sarstedt, & Ringle, 2019), indicating that the measurement tool is highly reliable.

At the same time, the average variance extracted (AVE) is over 0.5 (Table 5), proving the convergent validity of the data. Given that the discriminant validity test criteria of Fornell and Larcker (1981) may be insufficient; this study uses the Hetero-Trait-Mono-Trait (HTMT) ratio assessment (Henseler, Ringle, & Sarstedt, 2015). The results show that all HTMT ratios are below the threshold of 1 (Hair et al., 2019) (Table 6), supporting good differentiation between constructs.

In summary, the model constructs can be effectively distinguished at the empirical level.

Table 5. Construct reliability and validity.

	Items	Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
First-order construct						
IN	IN1	0.791	0.894	0.896	0.916	0.576
	IN2	0.802				
	IN3	0.754				
	IN4	0.800				
	IN5	0.762				
	IN6	0.719				
	IN7	0.706				
	IN8	0.731				
NI	NI1	0.832	0.884	0.889	0.920	0.742
	NI2	0.881				
	NI3	0.893				
	NI4	0.840				
PCDC	PCDC 1	0.828	0.781	0.787	0.859	0.605
	PCDC 2	0.770				
	PCDC 3	0.718				
	PCDC 4	0.791				
PCIA	PCIA 1	0.770	0.710	0.710	0.838	0.633
	PCIA 2	0.808				
	PCIA 3	0.808				
PH	PH1	0.855	0.877	0.879	0.915	0.730
	PH2	0.847				
	PH3	0.823				
	PH4	0.892				
SC	SC1	0.826	0.892	0.895	0.920	0.698
	SC2	0.806				
	SC3	0.837				
	SC4	0.842				
	SC5	0.865				
SI	SI1	0.810	0.872	0.878	0.904	0.610
	SI2	0.740				
	SI3	0.732				
	SI4	0.808				
	SI5	0.786				
	SI6	0.808				
T	T1	0.758	0.784	0.789	0.860	0.605
	T2	0.770				
	T3	0.781				
	T4	0.803				
Second-order construct						
PC	PCDC	0.892	0.715	0.718	0.875	0.778
	PCIA	0.872				

Note: Inertia (IN); National identity (NI); Privacy concern data collection (PCDC); Privacy concern improper access (PCIA); Privacy concern (PC); Payment habit (PH); Switching cost (SC); Switching intention (SI); Trust (T).

Table 6. Heterotrait-Monotrait Ratio (HTMT).

First-order construct	IN	NI	PCDC	PCIA	PH	SC	SI	T
IN								
NI	0.066							
PCDC	0.093	0.322						
PCIA	0.073	0.240	0.744					
PH	0.609	0.044	0.201	0.181				
SC	0.550	0.038	0.132	0.115	0.454			
SI	0.203	0.298	0.559	0.546	0.133	0.151		
T	0.074	0.335	0.502	0.519	0.083	0.102	0.513	
Second-order construct	IN	NI	PC	PH	SC	SI	T	
IN								
NI	0.018							
PC	0.062	0.314						
PH	0.540	0.006	0.202					
SC	0.494	0.011	0.129	0.404				
SI	0.179	0.270	0.601	0.112	0.132			
T	0.000	0.273	0.527	0.024	0.065	0.438		

Note: Inertia (IN); National identity (NI); Privacy concern data collection (PCDC); Privacy concern improper access (PCIA); Privacy concern (PC); Payment habit (PH); Switching cost (SC); Switching intention (SI); Trust (T).

5.3. Internal Structural Model

This study employed bootstrapping with 5,000 subsamples to rigorously test and validate the structural model. The results, presented in Table 7, indicate that all hypothesized relationships were supported except for H6. For the supported hypotheses, the corresponding p-values were well below the 0.01 threshold, reinforcing the robustness of the findings. Specifically, privacy concern ($\beta = 0.361$, $p < 0.001$) and trust ($\beta = 0.247$, $p < 0.001$) exerted significant positive effects on switching intention, while inertia ($\beta = -0.162$, $p < 0.01$) demonstrated a significant negative effect. Furthermore, payment habits ($\beta = 0.407$, $p < 0.001$) and switching costs ($\beta = 0.330$, $p < 0.001$) were both found to positively influence inertia.

Table 7. Hypothesis testing.

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1	PC -> SI	0.361	0.360	0.057	6.331	0.000	Supported
H2	PH -> IN	0.407	0.406	0.054	7.493	0.000	Supported
H3	SC -> IN	0.330	0.330	0.055	5.968	0.000	Supported
H4	IN -> SI	-0.162	-0.162	0.050	3.227	0.001	Supported
H5	T -> SI	0.247	0.248	0.051	4.881	0.000	Supported
H6	NI -> SI	0.109	0.109	0.059	1.827	0.068	Unsupported

Note: Inertia (IN); National identity (NI); Privacy concern (PC); Payment habit (PH); Switching cost (SC); Switching intention (SI); Trust (T).

5.4. Predictive Relevance and Effect Size

To assess the robustness of the structural model, Table 8 reports the coefficient of determination (R^2) and cross-validated redundancy (Q^2), following the guidelines of Hair et al. (2019). According to these standards, R^2 values of 0.75, 0.50, and 0.25 reflect strong, moderate, and weak explanatory power, respectively. In this study, the R^2 values for inertia ($R^2 = 0.383$) and switching intention ($R^2 = 0.350$) approach the moderate level, suggesting a reasonable explanatory capacity. In addition, all Q^2 values were positive, confirming the model's predictive relevance for the endogenous constructs (Hair et al., 2019). Regarding relative effects (f^2), the results in Table 9 show that, with the exception of national identity, all variables exceed (Cohen, 1988) 0.02 threshold, indicating medium to large effect sizes. This suggests that these predictors make meaningful contributions to explaining the dependent variable.

Table 8. Determination coefficient and cross-validated redundancy analysis.

Construct	R-square	R-square adjusted	SSE	Q^2 (=1-SSE/SSO)
IN	0.383	0.380	225.415	0.374
SI	0.350	0.343	243.819	0.323

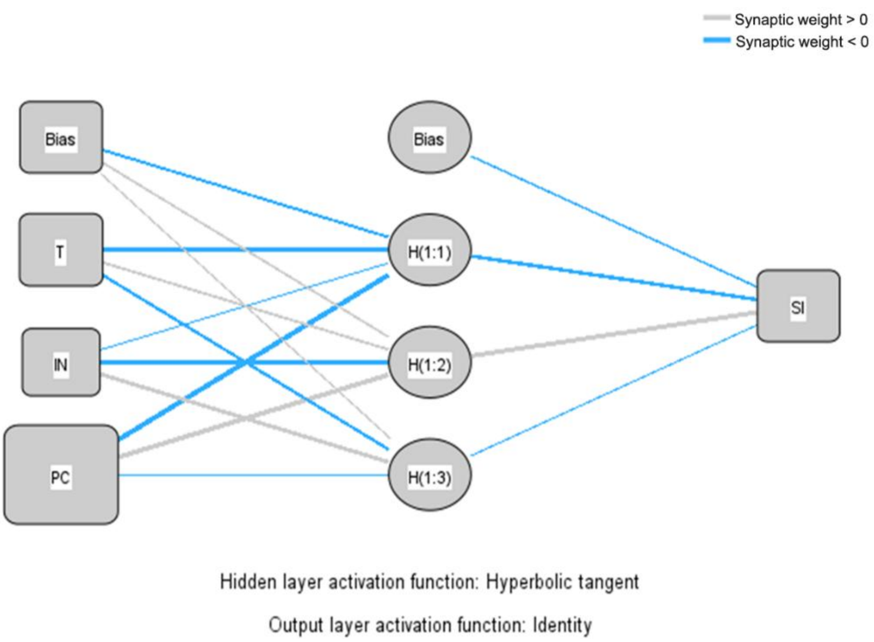
Table 9. Effect size (F^2)

Path	f-square
IN -> SI	0.040
NI -> SI	0.016
PC -> SI	0.155
PH -> IN	0.225
SC -> IN	0.148
T -> SI	0.073

5.5. Artificial Neural Network (ANN) Analysis

Haykin (1999) defined artificial neural networks (ANNs) as algorithms designed to mimic the functioning of the human brain. Unlike regression analysis, ANNs are capable of handling non-compensatory decision processes and do not rely on assumptions of normal data distribution. In this study, a multi-layer perceptron (MLP) artificial neural network (ANN) architecture was employed, operating on a feedforward backpropagation (FFBP) mechanism and consisting of an input layer, hidden layer, and output layer (Leong et al., 2025). The MLP model applied a sigmoid activation function, facilitating the transfer and processing of information through weighted synaptic connections.

To mitigate overfitting, a 10-fold cross-validation strategy was adopted: 90% of the dataset was used for training, while the remaining 10% was reserved for testing the model's generalization capability. Figure 2 illustrates the representative computational process of the ANN analysis. Model performance was assessed using the root mean square error (RMSE), where lower values indicate higher predictive accuracy (see Table 10). Furthermore, Table 11 details the relative contribution of each predictor variable to the overall predictive performance of the ANN, offering insights into the behavioral dynamics underpinning the model. Notably, the predictive outcomes derived from ANN analysis were consistent with those obtained through partial least squares structural equation modeling (PLS-SEM), thereby reinforcing the robustness of the findings.



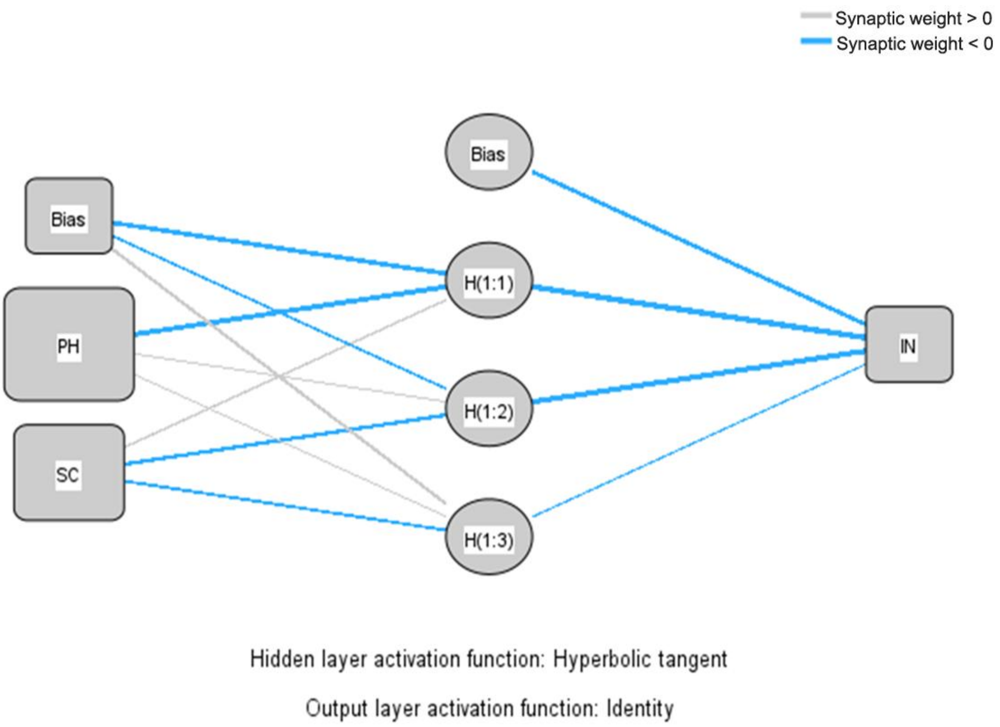


Figure 2. ANN analysis.

Note: Inertia (IN); Privacy concern (PC); Payment habit (PH); Switching cost (SC); Switching intention (SI); Trust (T).

Table 10. RMSE value of 10-fold ANN models.

Neutral network	Model A		Model B	
	Input: PC, IN, T		Input: PH, SC	
	Output: SI		Output: IN	
	Training	Testing	Training	Testing
Neural network	RMSE	RMSE	RMSE	RMSE
ANN1	0.5686	0.5593	0.5414	0.5030
ANN2	0.5813	0.4555	0.5414	0.5727
ANN3	0.5798	0.4841	0.5276	0.6179
ANN4	0.5858	0.5532	0.5510	0.5170
ANN5	0.5777	0.5197	0.5700	0.5197
ANN6	0.5856	0.7045	0.5378	0.5889
ANN7	0.5953	0.5211	0.5377	0.4598
ANN8	0.5802	0.5044	0.5286	0.5584
ANN9	0.5842	0.4790	0.5915	0.4417
ANN10	0.5847	0.6042	0.5642	0.4227
Mean	0.5823	0.5385	0.5491	0.5202
SD	0.0068	0.0728	0.0204	0.0651

Note: Inertia (IN); Privacy concern (PC); Payment habit (PH); Switching cost (SC); Switching intention (SI); Trust (T).

Table 11. Sensitivity analysis.

PLS path	Original sample (o)/Path coefficient	ANN results: normalized relative importance (%)	Ranking (PLS-SEM) [based on path coefficient]	Ranking (ANN) [based on normalized relative importance]	Remark
Model A					
PC->SI	0.361	100.000%	1	1	Match
IN->SI	-0.162	30.138%	3	3	Match
T->SI	0.247	52.095%	2	2	Match
Model B					
PH->IN	0.407	100.000%	1	1	Match
SC->IN	0.330	70.827%	2	2	Match

Note: Inertia (IN); Privacy concern (PC); Payment habit (PH); Switching cost (SC); Switching intention (SI); Trust (T).

5.6. Fuzzy Set Qualitative Comparative Analysis (fsQCA)

5.6.1. Calibration Data

When using fuzzy set qualitative comparative analysis (fsQCA), researchers need to calibrate the data first. According to Ragin (2009), the seven-level Likert scale data is converted into a fuzzy set between 0 and 1. Among them, "1" represents complete membership and "0" represents non-membership. There are various calibration standards. Li et al. (2022) and (Pappas & Woodside, 2021) suggest that "6", "4", and "2" correspond to "1", "0.5", and "0". However, fixed scale calibration may be inaccurate under non-normal distribution data. Greckhamer, Furnari, Fiss, and Aguilera (2018) emphasized that calibration should be "semi-theoretical and semi-empirical" to reflect the differences between cases. Therefore, we advocate individualized calibration. This study uses the 95%, 50%, and 5% percentiles of each factor to define complete membership, moderate membership, and non-membership (Pappas & Woodside, 2021).

5.6.2. Necessity Analysis

The core purpose of necessity analysis is to evaluate whether a variable is an indispensable element for achieving the target outcome (Ragin, 2009). In this study, we established switching intention (SI) as the main outcome variable for analysis. At the same time, several exogenous variables were introduced as potential antecedents, including privacy concern (PC), inertia (IN), trust (T), and national identity (NI), which are the key antecedents affecting switching intention (SI) (see Table 12). According to the theoretical framework of Ragin (2009), if the consistency level of a variable exceeds 0.9, it strongly indicates that the antecedent is a necessary condition for the occurrence of the outcome. In addition, to evaluate the sufficiency of the antecedent, the concept of coverage is introduced. This indicator reflects the proportion of a specific antecedent variable in the effective explanation of the outcome, which is an important yardstick for measuring its explanatory power.

Table 12. Necessity analysis of conditions.

Condition	SI		~SI	
	Consistency	Coverage	Consistency	Coverage
PC	0.788	0.792	0.561	0.607
~PC	0.608	0.564	0.808	0.804
IN	0.618	0.596	0.694	0.719
~IN	0.709	0.683	0.610	0.632
T	0.756	0.773	0.574	0.631
~T	0.638	0.582	0.793	0.778
NI	0.753	0.758	0.588	0.637
~NI	0.639	0.591	0.777	0.771

Note: Inertia (IN); National identity (NI); Privacy concern (PC); Trust (T).

5.6.3. fsQCA Results

To obtain the fsQCA configuration results, we constructed a truth table to list all possible combinations that may lead to an increase in user switching intention (SI), and screened out combinations with a frequency of less than 3 times. When the sample size is large, too low a frequency will result in solutions that are too complex to interpret. When the sample size exceeds 150, it is recommended that the frequency be greater than 3 times before being retained (Pappas & Woodside, 2021). A raw consistency threshold of 0.85 (Pappas & Woodside, 2021) was set to determine which combinations can lead to an increase in SI. Then, the Quine-McCluskey algorithm was used to generate simple solutions, intermediate solutions, and complex solutions. Complex solutions contain all possible configurations, and interpreting complex configurations is quite difficult (Fiss, 2011). Therefore, the focus is on simple solutions and intermediate solutions (Pappas & Woodside, 2021). Simple solutions highlight key conditions, while intermediate solutions combine theory and experience to clarify the influence of peripheral conditions. Table 13 shows the fsQCA solution, where large black dots (●) represent core causes and conditions that have a direct impact on the results;

small black dots (•) represent peripheral causes and conditions that have an indirect impact on the results. Cross points (⊗) indicate that the conditions leading to the results do not exist or are denied. In addition, blank spaces indicate that the respondents are neutral about the existence or non-existence of the condition (Pappas & Woodside, 2021). Finally, for switching intention, fsQCA generated three solutions with an overall consistency of 0.810850 and an overall coverage of 0.808888, which indicates that the obtained solutions can effectively explain most cases of users' switching intention in this study.

Table 13. fsQCA analysis.

Condition	Solution1	Solution2	Solution3
PC	●	●	
IN	⊗		
T		●	●
NI			●
Raw coverage	0.580	0.659	0.625
Unique coverage	0.085	0.033	0.065
Consistency	0.8695	0.859	0.863
Solution coverage	0.809		
Solution consistency	0.811		

Note: Inertia (IN); National identity (NI); Privacy concern (PC); Trust (T). ● = Core causes and conditions; • = Peripheral causes and conditions; ⊗ = Absence of condition; blank = Neutral/Irrelevant condition.

6. DISCUSSION

Based on the research question RQ1 of this paper: What features of third-party mobile payment cause users to switch to e-CNY payment? This study employs a systematic empirical method to verify the significant role of privacy concerns in influencing users to switch to e-CNY payment. The findings align with previous research results of Lenz et al. (2023); Vimalkumar et al. (2021); Jozani et al. (2020), and Xia et al. (2023), further strengthening the consensus within the theoretical community. Specifically, the central bank is more secure in user data management, which leads users of third-party mobile payments to worry about illegal access to their personal data and consider changing payment methods. Third-party mobile payment applications are profit-oriented and integrate multiple functions such as taxi hailing and restaurant reservations, which require collecting more personal information. Conversely, the central bank digital currency (CBDC) payment platform is non-profit, focuses solely on payment, and reduces unnecessary information collection. Therefore, users may be more concerned about information collection by third-party applications and seek alternative payment tools. To further explore this phenomenon, this study introduced a second-stage ANN analysis, which showed that privacy concerns predominantly influence users' switching intentions. This finding is consistent with the preliminary PLS-SEM analysis results. Finally, the fsQCA analysis further confirmed the PLS-SEM findings, indicating that privacy concerns were a parsimonious solution in both Solution 1 and Solution 2. This underscores the significant impact of privacy concerns on users' switching intentions. CBDC payment designers should address the shortcomings of third-party mobile payments, enhance the advantages of e-CNY payment, and focus on reducing user privacy concerns. They can implement encryption technology to ensure transaction security, establish transparent privacy policies, provide user-controllable privacy settings, and introduce anonymous payment mechanisms. These measures should be combined to effectively reduce user privacy concerns and promote the adoption and development of e-CNY payment.

Based on the research question RQ2 of this paper: What features of third-party mobile payments prevent users from switching to e-CNY payment? This study verified the significant role of inertia in preventing users from switching to e-CNY payment through a systematic empirical method. This finding is consistent with the previous research results of Hsieh (2021) and Kumar et al. (2021), further strengthening the consensus in the theoretical community. Specifically, users continue to use existing payment tools due to behavioural inertia and form habits due to long-term use. Cognitive inertia makes users tend to maintain the status quo even if they realize the advantages of other payment methods such as e-CNY, showing conservatism, stability, and resistance to change. Emotional inertia makes users stick to the current tools due to uncertainty, pressure, or emotional connection to switching payment tools. Behavioural, cognitive, and emotional inertia jointly hinder users from accepting and adopting the e-CNY payment system. At the same time, this study verifies that payment habit and switching cost are the main factors affecting inertia. This study introduced the second-stage ANN analysis, and the results showed that inertia ranked third among the many factors affecting users' conversion intention. This finding is consistent with the results of the preliminary PLS-SEM analysis. Finally, the results of the fsQCA analysis further confirmed the PLS-SEM analysis, and inertia was a parsimonious solution in Solution 1. It further confirmed that inertia is an important obstacle to users' switching intention. To increase the usage rate of e-CNY payment, designers need to take measures to change users' payment habits and reduce switching costs. It is necessary to understand user preferences, launch promotional activities to increase attractiveness, and optimize the payment process to increase convenience. At the same time, provide operation guides, optimize payment interfaces, and offer convenient account migration services to reduce learning, time, and financial costs. These measures will help break payment inertia and increase e-CNY usage.

According to the research question RQ3 of this paper: What features of e-CNY payment attract users to switch from third-party mobile payment to e-CNY payment? The study verified the significant role of trust in attracting users to switch from third-party mobile payment to e-CNY payment through a systematic empirical method. This finding is consistent with the previous research results of Cui et al. (2023) and Lin and Wang (2017), further strengthening the consensus in the theoretical community. Specifically, after users trust the security and stability of the e-CNY payment system, they will be more inclined to adopt it as a means of payment. Trust enhances confidence in use and stimulates willingness to try. Therefore, as trust increases, users' intention to switch to e-CNY will also increase. At the same time, the impact of national identity on switching intention was not confirmed in this study. The possible reason is that e-CNY payment is in its early stages, market popularization and user education are insufficient, the user base is weak, and usage habits have not been formed. Despite national promotion, users do not have a deep understanding of e-CNY as a national digital financial innovation and lack national identity. This study introduced a second-stage ANN analysis, and the results showed that trust ranked second among the many factors that affect users' switching intention. This finding is consistent with the results of the preliminary PLS-SEM analysis. Finally, the results of the fsQCA analysis further confirmed the PLS-SEM analysis, and trust was a parsimonious solution in both Solution 2 and Solution 3. This further confirmed the important impact of trust on users' switching intention. Designers need to take measures to improve users' trust in e-CNY payment, including strengthening security mechanisms, improving system stability, optimizing user experience, and responding to user feedback. At the same time, a transparent information disclosure mechanism should be introduced to enhance users' understanding and trust in e-CNY payment as a national digital financial innovation.

7. SIGNIFICANCE

This study offers significant theoretical contributions to the field of CBDC payments, addressing a notable gap in the literature. While growing scholarly attention has highlighted the multidimensional influence of CBDC technologies and their potential to transform various aspects of social and economic life, little research has explicitly examined users' switching intentions. By focusing on this underexplored perspective, the study broadens the theoretical boundaries of CBDC research. Integrating constructs such as privacy concerns, payment habits, switching costs, inertia, trust, and national identity, the study develops a tailored research framework that elucidates the mechanisms shaping user switching behavior. This framework not only provides a novel lens for understanding behavioral decision-making but also enriches the knowledge system of CBDC research by setting an example for future studies in this emerging domain.

At the methodological level, the study makes an equally noteworthy contribution by advancing beyond the constraints of traditional linear models. It introduces a composite three-stage analytical approach PLS-ANN-fsQCA that combines the strengths of partial least squares modeling, artificial neural networks, and fuzzy-set qualitative comparative analysis. This design retains the linear and compensatory advantages of PLS, incorporates the nonlinear and non-compensatory features of ANN (Leong, Chen, Willer, & Zaki, 2020) and leverages the configurational insights of fsQCA to identify multiple causal pathways (Pappas & Woodside, 2021). Collectively, this synthesis expands the analytical dimension of CBDC research, enabling a more comprehensive exploration of linear, nonlinear, and configurational effects. By adopting this innovative framework, the study not only deepens understanding of user behavior but also establishes a robust methodological foundation for future inquiry into complex decision-making processes.

From a practical standpoint, the findings carry direct implications for the promotion of e-CNY. First, the results confirm that privacy concerns strongly influence switching behavior, underscoring the need for designers to reduce such concerns by enhancing encryption protocols, providing transparent privacy policies, offering controllable settings, and facilitating anonymous transactions. Second, inertia is shown to be a critical barrier to adoption. To mitigate this, practitioners should improve user guidance, streamline onboarding processes, optimize interfaces, and provide account migration services, while also strengthening promotional strategies. Finally, trust emerges as a decisive pull factor. Building and sustaining trust will require ongoing investment in security mechanisms, system stability, user experience enhancement, and transparent information disclosure. Together, these insights offer actionable strategies for fostering user confidence and encouraging wider adoption of e-CNY.

8. LIMITATIONS

This study has several limitations that warrant careful consideration. The primary limitation is its cross-sectional research design, which focuses solely on the status of CBDC payment conversion intention at a specific point in time. Since China is currently in the initial development stage of CBDC payment, the field is highly dynamic, and the current findings may undergo significant changes over time. Despite the methodological strengths of this study, two important limitations should be emphasized. First, the use of a cross-sectional survey design restricts the ability to capture temporal shifts in user attitudes and behaviors toward CBDC payments. Users' perceptions of trust, privacy, and inertia may evolve as the e-CNY matures and as broader economic conditions change. Therefore, longitudinal studies would be valuable for tracing adoption dynamics over time. Second, the data collection scope is limited to China, which affects the understanding of differences in CBDC payment conversion intentions across various cultural contexts. While this study concentrates on the Chinese context, the findings offer lessons for other central banks worldwide. Issues related to privacy, trust, and switching inertia are not unique to China and should be carefully addressed in the design and implementation of CBDCs in other jurisdictions. To address this limitation and enhance the generalizability and cross-cultural understanding of the model, future research should focus on cross-border comparisons and include national samples from diverse cultural backgrounds to fully explore the multiple influencing factors and variability of CBDC payment conversion intentions.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
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