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# TRUST, SECURITY, USEFULNESS, EASE-OF-USE AND DIGITAL LENDING ADOPTION: THE MODERATING ROLE OF FINANCIAL LITERACY AND INCOME LEVEL

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## ABSTRACT

***This study develops and tests an extended Technology Acceptance Model (TAM) for digital retail lending adoption by integrating two additional critical constructs perceived privacy and security and perceived trust and examining the co-moderating effects of financial literacy and income level. Using survey data from 448 customers of a large commercial bank in Thailand, the model was estimated via partial least squares structural equation modeling and multigroup analysis. The findings indicate that perceived usefulness has the highest influence on digital lending adoption intention, while perceived privacy and security exert the strongest total effect when indirect influences are considered. Perceived trust demonstrates indirect effects on adoption through other factors as well. Moderation analysis reveals distinct adoption drivers across four income-literacy segments. The results offer segment-specific guidance for lenders and policymakers to enhance platform usability, trust, and security, tailored to users' financial literacy and income levels, thereby promoting digital lending inclusion.***

**KEYWORDS:** Perceived Usefulness, Perceived Ease-of-Use, Perceived Self-Efficacy, Perceived Trust, Perceived Privacy and Security, Behavioral Intention, Technology Acceptance Model, Digital Lending.

## 1. INTRODUCTION

Recent advancements in digital technologies have transformed the financial domain, with digital lending emerging as a prominent trend. Thailand, as a rapidly digitizing economy, has witnessed a surge in digital lending platforms.

The "Digital 2023: Global Overview Report" by Hootsuite and We Are Social highlights that there are 5.44 billion unique mobile phone users globally, with a 69.3% penetration rate. In Thailand, 50.5 million banking and financial service applications are used monthly, accounting for 72.1% of the Thai population, compared to the global average of 40.2%. Thailand leads globally in banking and financial services applications, with mobile banking users growing from 0.52 million in 2010 to 63.5 million by 2021 (Bank of Thailand, 2022).

Despite leading in mobile banking, digital lending in Thailand remains nascent. The Kasikorn Research Center (2022) estimated the market value of digital lending to be approximately THB 14.0-15.5 billion in 2022, comprising only 0.3% of the total retail loan volume. Unlike mobile banking, which simplifies transactions, digital lending involves more complex processes, such as inputting personal data and attaching documents, which can deter users. Additionally, Bank of Thailand regulations necessitate proof of income or debt servicing ability, primarily non-digitalized in Thailand.

Understanding digital lending adoption behavior is crucial for economic growth and financial inclusion, especially in emerging markets. Digital lending can enhance access to credit, driving entrepreneurship and economic activity (Frost, 2020; Haddad and Hornuf, 2019), and bridge the gap for underserved populations, promoting inclusive financial systems (Ozili, 2018). Addressing privacy, security, and regulatory challenges can significantly boost adoption rates and contribute to a more inclusive economy.

## 2. THEORETICAL FOUNDATION

To better understand the factors influencing digital lending adoption behavior, this study extends the Technology **Acceptance Model (TAM) by incorporating two additional constructs** perceived privacy and security (PPS) and perceived trust (PT).

This research builds on the established TAM framework, widely utilized in the context of digital financial services (Bhatiasevi, 2015). Existing literature suggests that digital lending adoption is influenced by perceived usefulness (PU), perceived ease of use (PEOU), and users' trust in the platform and their concerns about privacy and security (Bhatiasevi, 2015; Rathnaweera and Karunasena, 2020).

### *2.1. Technology Acceptance Model (TAM)*

Introduced by Davis (1989), TAM is a leading model in financial services innovation adoption studies (Adistyasari et al., 2020; Hoang et al., 2021; Hu et al., 2019; Lee, 2017). TAM posits that actual system use is determined by users' attitudes, influenced by PU and PEOU. Davis (1989) defined PU as the belief that using a system enhances job performance and PEOU as the ease of using the system without effort.

Subsequent research found that attitudes partially mediate actual system use, leading to the "Parsimonious TAM" where "Attitude Toward Using" (ATU) is replaced with "Behavioral Intention" (BI). This model emphasizes that substantial PU directly influences BI, bypassing the need for forming attitudes (Davis, 1989). TAM's simplicity and predictive power have made it a widely cited theory with extensive reviews (Chuttur, 2009; King and He, 2006; Lee et al., 2003; Legris et al., 2003; Marangunić and Granić, 2015; Schepers and Wetzels, 2007; Sharp, 2006; Turner et al., 2010).

Studies have extended TAM by adding constructs such as self-efficacy, technology anxiety, subjective norms, expectations, perceived risk, and trust to enhance its predictive validity (Marangunić and Granić, 2015). Constructs like PT have proven significant in predicting digital lending adoption (Rathnaweera and Karunasena, 2020).

### *2.2. Perceived Privacy and Security (PPS) and Perceived Trust (PT)*

PPS, a formative construct composed of perceived privacy (PP) and perceived security (PS), is crucial in digital lending. Concerns regarding data privacy and security are significant barriers to adoption (Chen, 2013). Users' perceptions of how their personal information is handled and secured can significantly impact their willingness to use digital lending platforms (Bélanger and Crossler, 2011; Pavlou, 2011). Addressing these concerns can enhance user trust and adoption rates, promoting financial inclusion and economic growth in emerging markets (Frost, 2020; Haddad and Hornuf, 2019; Ozili, 2018).

Perceived Trust (PT) captures beliefs about a platform and provider's competence, integrity, and benevolence, reducing perceived risk in technology-mediated transactions. Trust has long been integrated with TAM in e-commerce, where it complements perceived usefulness (PU) and ease-of-use (PEOU) by lowering uncertainty in high-stakes

decisions (Pavlou, 2003).

Incorporate Perceived Privacy and Security (PPS) and Perceived Trust (PT) with TAM

Empirically, privacy and security foster trust, and trust, in turn, increases PU/PEOU and downstream intentions. Meta-analyses and reviews consistently report that perceived privacy and security influence perceived trust and perceived trust leads to behavioral intention/continued use, with partial mediation through PU/PEOU depending on context (Kim and Peterson, 2017 and Jafri et al., 2024).

Compared with mobile payments/deposits, digital lending entails data-intensive underwriting and automated credit decisions, heightening sensitivity to both data privacy and platform security, and amplifying the role of trust in provider conduct and algorithmic fairness. Prior digital-lending adoption studies often extend TAM with perceived privacy and security or with trust, but rarely treat PPS and PT jointly or examine their interplay. For example, Yadav and Shanmugam (2024) add perceived security and risk to TAM without explicitly modeling trust, while Asamani and Majumdar (2024) identify trust as pivotal yet do not operationalize privacy and security as a unified PPS construct. Bringing PPS and PT together within TAM is therefore theoretically warranted and contextually salient for digital lending.

### *2.3. Financial Literacy*

Financial literacy refers to the understanding of financial concepts and risks, enabling informed decision-making. Higher financial literacy enhances users' ability to comprehend the benefits and risks of digital lending, increasing their PT and PEOU (Lusardi and Mitchell, 2014). Financially literate consumers are more likely to appreciate the value proposition of digital lending, reducing resistance to adoption and enhancing BI (Klapper et al., 2015).

### *2.4. Income Level*

Income level influences an individual's capacity to access and utilize financial services. Higher income levels provide more financial stability, making digital lending more accessible due to individuals' ability to meet the criteria and service debt (Beck et al., 2009). Conversely, lower-income individuals may face barriers such as a lack of digital access or skepticism toward new financial technologies. The interaction between income level and PPS is also significant, as individuals with higher incomes may demand more robust security features to protect their financial information (Demirguc-Kunt et al., 2018).

Understanding these factors can help improve digital lending adoption, leading to better economic outcomes and financial inclusion, especially in emerging markets where digital financial services can bridge significant gaps (Frost, 2020; Haddad and Hornuf, 2019; Ozili, 2018).

### *2.5 Research Questions*

This study aims to investigate the factors influencing the adoption of digital lending in Thailand by extending the TAM. The proposed research model includes PT and PPS as antecedent constructs and considers the moderating effects of financial literacy and income level. The key research questions in this study are as follows.

1. What are the primary factors influencing the adoption of digital lending platforms in Thailand?
2. How do perceived trust (PT) and perceived privacy and security (PPS) impact users' willingness to adopt digital lending services?
3. How do financial literacy and income level moderate the adoption of digital lending platforms?

By addressing these research questions, this study seeks to provide a comprehensive understanding of the factors driving digital lending adoption in Thailand, offering insights that could enhance financial inclusion and economic growth in emerging markets.

## 3. RESEARCH MODEL AND HYPOTHESES

The TAM, introduced by Davis (1989), has been extensively used to explain consumer BIs using PU and PEOU. However, studies argue that TAM might omit crucial variables relevant to mobile banking and digital lending adoption studies. For instance, Luarn and Lin (2005) extended TAM by including perceived credibility, perceived self-efficacy (PSE), and perceived financial costs. Akturan and Tezcan (2012) incorporated perceived benefits and perceived risks to study mobile banking adoption among young adults. Gu et al. (2009) incorporated trust constructs such as trust in technologies, vendors, and structural assurance to better explain adoption. The role of service quality, satisfaction, and trust as drivers of loyalty in banking contexts (Boonlertvanich, 2018) further underscores the need to consider these factors in digital lending adoption studies.

### *3.1. Perceived Usefulness (PU)*

PU has consistently been significant in explaining usage intentions across various contexts, including digital lending (Davis, 1989; Luarn and Lin, 2005; Sharma, 2019; Yuan et al., 2016). Consumers are

likely to adopt digital lending applications if they perceive these platforms as effective tools that provide financial flexibility anytime, anywhere. **Therefore, the following hypothesis was proposed**

H1: PU positively affects the BI to use digital lending.

### *3.2. Perceived Ease of Use (PEOU)*

PEOU is another critical construct in TAM, significantly influencing BI (Davis, 1989). Empirical evidence supports its importance in digital lending adoption (Luarn and Lin, 2005; Sharma, 2019; Sheng et al., 2011). Because digital lending requires additional effort to complete applications compared to routine mobile banking services, financial institutions must enhance their platforms to improve PEOU and drive adoption. **Therefore, the following hypotheses were proposed**

H2: PEOU positively affects the PU of digital lending.

H3: PEOU positively affects the BI to use digital lending.

### *3.3. Perceived Self-Efficacy (PSE)*

PSE refers to the belief in one's capability to perform a specific task (Compeau and Higgins, 1995). In digital lending, PSE reflects consumers' confidence in independently using financial applications. Higher PSE enhances PEOU and BI (Igbaria and Iivari, 1995; Venkatesh, 2000). Traditionally in Thailand, customers relied on bank officers for loan applications, a process limited by branch office hours. Digital lending aims to offer greater flexibility, but it requires customers to navigate the process independently. Financial institutions must simplify the application process to bolster PSE. **Therefore, the following hypotheses were proposed**

H4: PSE positively affects the PEOU of digital lending.

H5: PSE positively affects BI to use digital lending.

### *3.4. Perceived Trust (PT)*

Trust is an individual's belief that others will act as expected, mitigating perceived risks and fraud (Grazioli and Jarvenpaa, 2000; Pavlou, 2003). Trust is crucial for digital lending adoption (Baptista and Oliveira, 2016; Liu et al., 2019). Thailand is becoming more digitalized from the digital infrastructure development fostered by the government policy, introduction of international mobile commerce, and the ride-hailing platform. However, increasing digital adoption has also led to higher financial transaction fraud, raising concerns about using digital lending services (Kraiwanit and Srijaem, 2021).

Research indicates that PT is an antecedent construct in the TAM and has a direct effect on all other constructs within the model. PT directly influences PU as consumers are more likely to perceive a service as beneficial if they trust it (Gefen, Karahanna, & Straub, 2003). PT also impacts PEOU because a trusted platform reduces perceived complexity and uncertainty, making the service easier to use (Gefen et al., 2003). Additionally, PT enhances PSE by fostering confidence in users' ability to successfully engage with the platform (Yousafzai, Pallister, & Foxall, 2005). Therefore, trust significantly influences BI by reducing perceived risks and enhancing users' willingness to adopt digital lending services (Baptista and Oliveira, 2016; Pavlou, 2003). The relationship between service quality, satisfaction, trust, and loyalty, as discussed by Boonlertvanich (2018), further supports the importance of trust in consumer financial behaviors.

Therefore, **the following hypotheses were proposed**

H6: PT positively affects PU of digital lending.

H7: PT positively affects PEOU of digital lending.

H8: PT positively affects PSE on use of digital lending.

H9: PT positively affects BI to use digital lending.

### *3.5. Perceived Privacy and Security (PPS)*

Perceived privacy (PP) and perceived security (PS) together form the construct of PPS, which is crucial for the adoption of digital lending platforms. Limbu et al. (2011) defined PP as consumers' perception regarding the protection of individually identifiable information on the internet and includes concerns regarding unauthorized sharing of personal information during online transactions. PS refers to consumers' perceptions about secure online transactions and protecting financial information from unauthorized access (Limbu et al., 2011), including potential financial crimes like theft of financial information, viruses, and malware (Sarel and Marmorstein, 2006).

Integrating these two constructs into PPS provides a more holistic understanding of users' concerns and their impact on digital service adoption (Dinev and Hart, 2006). Studies show that both PP and PS are critical in building trust and encouraging the use of digital platforms (Xu et al., 2012). When users feel confident that their personal and financial information is secure, they may perceive the technology as useful and easy to use, thereby enhancing their self-efficacy and intention to adopt

the technology (Kang and Lee, 2010; Li and Yeh, 2010; Zhou, 2013; Pavlou, 2003).

**Therefore, the following hypotheses were proposed**

H10: PPS positively affects PU of digital lending

H11: PPS positively affects PEOU of digital lending

H12: PPS positively affects PSE on using digital lending

H13: PPS positively affects BI on using digital lending

### *3.6. Moderating Variables: Financial Literacy and Income Level*

Financial Literacy. Financial literacy is crucial for consumers to make informed financial decisions and achieve optimal outcomes. It varies widely across the population, even in developed countries such as the United States. Lusardi and Mitchell (2014) developed questions regarding compounding, inflation, and investment diversification to assess Americans' financial literacy. Their study revealed significant gaps, particularly among vulnerable demographic segments such as the less educated, women, and minorities, resulting in poor financial decisions.

Conversely, consumers with higher financial knowledge may seek loans from digital channels, gaining benefits such as time savings in the application process and access to lower interest rates. Financial literacy enhances individuals' ability to assess the benefits and risks of digital lending, thereby increasing their PEOU and PU (Lusardi and Mitchell, 2014). Studies indicate that higher financial literacy levels correlate with better financial decision-making and greater confidence in using financial technologies (Remund, 2010; van Rooij et al., 2011). Concerning digital lending, financial literacy can help consumers evaluate the security and privacy measures of digital platforms, reducing perceived risk and increasing their BI to adopt these services (Klapper et al., 2015).

Income Level. Income level is another critical moderating variable influencing consumers' adoption of digital financial services. Higher income levels often correlate with better access to financial resources and technologies, facilitating the adoption of digital lending platforms. Such individuals may likely meet lending criteria and possess the financial stability necessary to engage with digital lending services (Beck et al., 2009). Income level can also shape consumers' perceptions of privacy and security. Higher-income individuals may demand more robust security features to protect their financial information, while lower-income individuals may emphasize the potential financial risks associated with digital lending (Demirguc-Kunt et al., 2018).

Interaction Effects. The interaction between financial literacy, income level, and the core constructs of TAM, PT, and PPS offers valuable insights into digital lending adoption behavior. For instance, financially literate individuals with higher incomes may perceive digital lending platforms as more useful and easier to use, leading to higher adoption rates. Conversely, individuals with lower financial literacy and income levels may require additional support and assurance regarding the security and privacy of digital lending services.

Understanding these moderating effects can help design targeted strategies that address the needs of different consumer segments, thereby enhancing financial inclusion and promoting economic growth in emerging markets.

## 4. CONCEPTUAL FRAMEWORK

Data were analyzed using partial least squares structural equation modeling (PLS-SEM) (Jöreskog, 1973; Wold, 1985). PLS, as an alternative to covariance-based SEM, has been widely applied in psychology, sociology, and other fields, including customer behavior (Fornell et al., 1996; Sohn and Moon, 2003). The PLS-SEM approach can dynamically handle various modeling challenges, especially concerning the stringent assumptions required by traditional multivariate statistics.

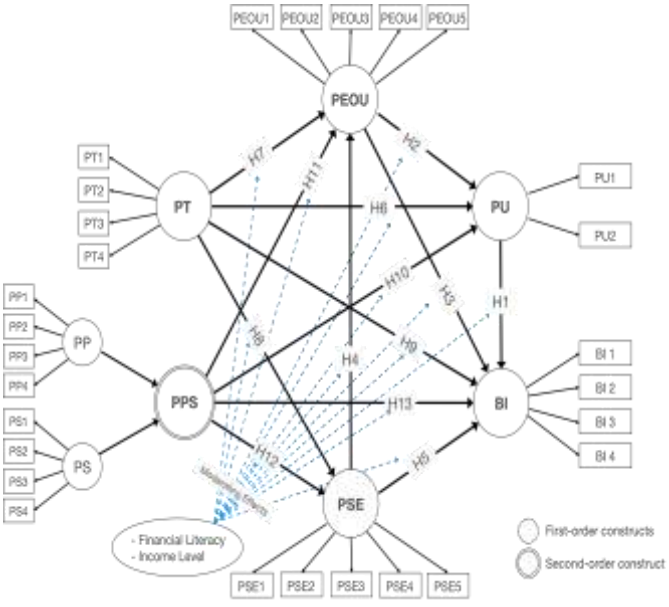


***Figure 1: Structural Model and Associated Hypotheses.***

Figure 1 illustrates the hypothesized model,

depicting each construct's underlying dimensions and their theorized causal relationships among constructs based on the literature reviewed. The solid lines represent the paths between the constructs of the inner structural model, while the dashed lines represent the outer measurement model of the reflective constructs.

### *4.1. The PLS-SEM Model*

The following structural equations corresponded to those shown in Figure 1

$\xi 1 = \beta 1 + \beta 12\, \xi 2 + \beta 13\, \xi 3 + \beta 14\, \xi 4 + \beta 15\, \xi 5 + \beta 16\, \xi 6 + \upsilon 1$,

$\xi 2 = \beta 2 + \beta 23\, \xi 3 + \beta 25\, \xi 5 + \beta 26\, \xi 6 + \upsilon 2$,

$\xi 3 = \beta 3 + \beta 34\, \xi 4 + \beta 35\, \xi 5 + \beta 36\, \xi 6 + \upsilon 3$,

$\xi 4 = \beta 4 + \beta 45\, \xi 5 + \beta 46\, \xi 6 + \upsilon 4$,

where $\xi 1$ is the BI, $\xi 2$ is the PU, $\xi 3$ is the PEOU, $\xi 4$ is the PSE, $\xi 5$ is the PT; and $\xi 6$ is the PPS

## 5. RESEARCH DESIGN AND METHODS

### *5.1. Sampling and Data Collection*

This study utilized a cross-sectional quantitative research design. Primary data were gathered through an online survey targeting Thai middle-income urban consumers, who are the primary market for retail lending by commercial banks.

**Data collection occurred in two phases** a pilot test and the main survey. The pilot test involved distributing physical questionnaires to 30 target respondents and experts to identify any ambiguities. Based on their feedback, the questionnaire was refined, and the main survey was subsequently conducted. A total of 448 valid samples were obtained from 500 distributed samples.

Most sample participants were female (58%); 42 years old or younger (58.9%); were single (35.4%); held a bachelor's degree (52.9%); were salary earners (89.7%); had an income below 30,000 baht per month (~850 USD) (52.4%); and had a debt-to-monthly income ratio of less than 35 (see Appendix A1).

Additionally, most respondents had bancassurance (68.8%), held fewer than two financial products (45.3%), and had some experience using digital channels (70%) (see Appendix A2). To measure the level of financial literacy, three assessment questions were adopted from Lusardi and Mitchell (2014). These questions evaluated the capability to calculate interest rates and understand inflation and risk diversification. The majority of respondents could accurately answer zero to one question (64.5%).

To ensure an adequate sample size for analyzing the moderating effects of financial literacy and income level, respondents who correctly answered zero to one financial literacy questions were classified as having low financial literacy (289 samples), while those who answered two to three questions correctly were classified as having high financial literacy (104 samples). For income level, respondents with a monthly income of less than 30,000 baht were classified as the low-income group (235 samples), while those with higher incomes were classified as the high-income group (213 samples).

### *5.2. Measures*

The questionnaire was developed based on existing literature, utilizing five-point Likert scales (Allen and Seaman, 2007; Edmondson, 2005; Likert, 1932). Given that studies on digital lending adoption are in the early stages, there is limited previous research in this specific area. Therefore, the questionnaire adapts elements from the original TAM and its extensions, which have been used to explain mobile banking adoption in the literature.

The questionnaire comprises seven sections, aligned with the constructs in the conceptual framework. Constructs from the parsimonious TAM model, including PU, PEOU, and BI, were measured using variables from Davis's (1989) research and its application in mobile banking (Akturan and Tezcan, 2012). PSE items were adapted from Compeau and Higgins (1995). PP and PS items were adapted from Chen (2013) and Kim and Peterson (2017), respectively. These constructs were combined to form the formative construct PPS. Appendix A4 lists the constructs and measured variables, along with their means and standard deviations.

### *5.3. PLS analysis*

The PLS model typically involves two stages (Hulland, 1999). The first stage evaluates the measurement model by performing validity and reliability analyses. **This stage was divided into two sub-analyses** first-order reflective measurement constructs and second-order formative measurement constructs. The first-order reflective constructs include PU, PEOU, PSE, PT, PP, PS, and BI. The second-order formative construct is the latent PPS, composed of PP and PS.

The second stage tested the structural model by estimating paths between constructs, assessing their significance, and determining the model's predictive capability. This sequence ensures the reliability and validity of the constructs before drawing conclusions about construct relationships.

Finally, multigroup analysis (MGA) was performed to analyze the moderating effects of financial literacy and income level. Differences in

direct, indirect, and total effects of each antecedent on BI were analyzed. To better understand the co-moderating role of the moderators, we first divided our samples into four subgroups having high- and low-financial literacy groups and high- and low-income level.

### *5.4. Outer Measurement Model Analysis*

PLS analysis of the research model was performed using SmartPLS (Ringle et al., 2005), allowing simultaneous testing of the outer measurement model and the inner structural model (Fornell and Bookstein, 1982).

The proposed model includes seven reflective constructs: PU, PEOU, PSE, PT, PP, PS, and BI. Indicator reliability was assessed using the factor loadings of each item, with a loading of 0.70 or higher indicating sufficient reliability (Hulland, 1999). Internal consistency was evaluated by calculating composite reliability (CR) and Cronbach's alpha for each construct, with scores above 0.70 considered reliable (Nunnally, 1978; Nunnally and Bernstein, 1994).

Table 1 shows the factor loadings for the latent variables: PU, PEOU, PSE, PT, PP, PS, and BI. PU, represented by PU1 and PU2, has perfect loadings of 1.000. PEOU, represented by PEOU1 to PEOU5, has loadings from 0.994 to 0.998. PSE, measured by PSE1 to PSE5, has loadings between 0.964 and 0.975. PT, assessed by PT1 to PT4, has loadings from 0.992 to 0.994. PP, represented by PP1 to PP4, has loadings from 0.949 to 1.000. PS, measured by PS1 to PS4, has loadings from 0.998 to 0.999. BI, represented by BI1 to BI4, has loadings from 0.981 to 0.990.

All factor loadings exceeded 0.70, with a minimum of 0.949, confirming indicator reliability. The high factor loadings demonstrated that the manifest variables accurately represent their respective latent variables, supporting the reliability and validity of the measurement model.

***Table 1: Factor Loadings of Outer Model: First-Order Latent Variables with Reflective Indicators.***

| Latent Variables | Manifest variables | Factor Loadings | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Perceived Usefulness (PU) | PU1 | 1.000 | | | | | | |
| | PU2 | 1.000 | | | | | | |
| Perceived Ease of Use (PEOU) | PEOU1 | | 0.995 | | | | | |
| | PEOU2 | | 0.997 | | | | | |
| | PEOU3 | | 0.998 | | | | | |
| | PEOU4 | | 0.995 | | | | | |
| | PEOU5 | | 0.994 | | | | | |
| Perceived Self-Efficacy (PSE) | PSE1 | | | 0.964 | | | | |
| | PSE2 | | | 0.967 | | | | |
| | PSE3 | | | 0.975 | | | | |
| | PSE4 | | | 0.971 | | | | |
| | PSE5 | | | 0.975 | | | | |
| Perceived Trust (PT) | PT1 | | | | 0.994 | | | |
| | PT2 | | | | 0.992 | | | |
| | PT3 | | | | 0.994 | | | |
| | PT4 | | | | 0.993 | | | |
| Perceived Privacy (PP) | PP1 | | | | | 1.000 | | |
| | PP2 | | | | | 0.998 | | |
| | PP3 | | | | | 1.000 | | |
| | PP4 | | | | | 0.949 | | |
| Perceived Security (PS) | PS1 | | | | | | 0.998 | |
| | PS2 | | | | | | 0.998 | |
| | PS3 | | | | | | 0.999 | |
| | PS4 | | | | | | 0.999 | |
| Behavioral Intention (BI) | BI1 | | | | | | | 0.981 |
| | BI2 | | | | | | | 0.990 |
| | BI3 | | | | | | | 0.988 |
| | BI4 | | | | | | | 0.990 |

Table 2 presents the reliability and validity statistics for the measurement model, including Cronbach's alpha (α), CR, and Average Variance Extracted (AVE) for the latent variables. All CR values exceed 0.80, ranging from 0.986 to 0.999, and all Cronbach's alpha values are above 0.70, ranging from 0.985 to 0.999. These high values confirm the internal consistency reliability of all constructs. Convergent validity, assessed through AVE, requires a minimum value of 0.50 (Chin, 1998). The AVE for all constructs ranges from 0.942 to 0.999, confirming that all measures exhibit satisfactory convergent validity.

**Discriminant validity was evaluated using three**

**established criteria** (1) cross-loadings of items as highest in their respective hypothesized constructs; (2) the square root of the AVE for each construct should exceed the construct's correlation coefficients with other constructs (Fornell and Larcker, 1981); and (3) the upper bound of the heterotrait-monotrait ratio (HTMT) from bootstrapping should be below 0.85, or in some cases, 0.90 (Henseler et al., 2015).

*Table 2: Reliability and Validity of the Outer Model.*

| Latent Variables | Cronbach's α | Composite reliability (CR) | Average Variance Extrated (AVE) |
|---|---|---|---|
| Perceived Usefulness (PU) | 0.999 | 0.999 | 0.999 |
| Perceived Ease of Use (PEOU) | 0.998 | 0.998 | 0.992 |
| Perceived Self-Efficacy (PSE) | 0.985 | 0.986 | 0.942 |
| Perceived Trust (PT) | 0.995 | 0.995 | 0.986 |
| Perceived Privacy (PP) | 0.999 | 0.999 | 0.998 |
| Perceived Security (PS) | 0.999 | 0.999 | 0.997 |
| Behavioral Intention (BI) | 0.991 | 0.992 | 0.975 |

For the first criterion, Appendix 5 presents the cross-loadings of all items, demonstrating that the highest loading for each item aligns with its hypothesized construct. This indicates that all outer constructs (PPS, PS, PU, PEOU, PSE, PT, and BI) are well-distinguished from each other, effectively measuring different aspects of user behavior and perceptions in digital lending.

For the second criterion, Table 3 displays the correlation matrix for the latent variables, with the square root of the AVE on the diagonal, ranging from 0.971 to 0.999, indicating strong convergent validity. The off-diagonal values represent the correlations between constructs. PU shows high correlations with PEOU (0.710) and BI (0.627). PEOU is substantially correlated with PSE (0.656) and PU (0.710). Additionally, PT correlates highly with PP (0.828) and PP with PS (0.818), reflecting the interconnectedness of trust, privacy, and security constructs. Since the square roots of all AVEs exceed the off-diagonal elements, this criterion is satisfactorily met.

*Table 3: Correlation Matrix: Discriminant Validity.*

| | PU | PEOU | PSE | PT | PP | PS | BI |
|---|---|---|---|---|---|---|---|
| PU | *1.000* | | | | | | |
| PEOU | 0.710 | *0.996* | | | | | |
| PSE | 0.611 | 0.656 | *0.971* | | | | |
| PT | 0.485 | 0.510 | 0.489 | *0.993* | | | |
| PP | 0.469 | 0.493 | 0.434 | 0.828 | *0.999* | | |
| PS | 0.528 | 0.563 | 0.482 | 0.733 | 0.818 | *0.999* | |
| BI | 0.627 | 0.619 | 0.547 | 0.551 | 0.544 | 0.587 | 0.987 |

Note: Square root of AVE is on the diagonal

For the third criterion, Table 4 shows the bootstrap results of the HTMT for each pair of constructs, whose values are all below the commonly accepted threshold of 0.85, indicating adequate discriminant validity among the constructs (Henseler et al., 2015). For example, the HTMT value between PU and PEOU is 0.711, between PU and PSE is 0.614, and between PU and BI is 0.63, all well below the 0.85 threshold. Similarly, the values between PT and PP (0.83), and PS and PP (0.818) are the highest in the table but still below the threshold. These values suggest that the constructs are distinct from each

other and that the model exhibits strong discriminant validity. This is further supported by the low HTMT values among other construct pairs, such as PT and PSE (0.492) and PP and PSE (0.437), reinforcing that each construct measures a unique aspect of the theoretical framework.

These correlations, along with the high AVE values, affirm the discriminant validity of the constructs, confirming that each latent variable is distinct and reliably measured. Our measurement model, therefore, demonstrates satisfactory discriminant validity.

Table 4: The HTMT of the Latent Variables.

| | PU | PEOU | PSE | PT | PP | PS | BI |
|---|---|---|---|---|---|---|---|
| PU | | | | | | | |
| PEOU | 0.711 | | | | | | |
| PSE | 0.614 | 0.66 | | | | | |
| PT | 0.486 | 0.511 | 0.492 | | | | |
| PP | 0.469 | 0.494 | 0.437 | 0.83 | | | |
| PS | 0.528 | 0.564 | 0.485 | 0.735 | 0.818 | | |
| BI | 0.63 | 0.622 | 0.552 | 0.554 | 0.547 | 0.59 | |

### *5.5. Inner Structural Model Analysis*

The second step involved evaluating the inner structural model, as shown in Table 6. The R2 values indicate the proportion of variance in the endogenous latent constructs explained by the model. The R2 values for PU, PEOU, PSE, and BI were 0.529, 0.502, 0.257, and 0.525, respectively (see factor loading and significance level in Figure 2). These results demonstrate that a substantial portion of the variance for PU, PEOU, and BI is explained by the model, as their R2 values exceed the 0.30 threshold, indicating substantial explanatory power (Chin, 1998). However, the R2 value for PSE is 0.257, which is slightly below the threshold but still acceptable within certain contexts. Overall, the high R2 values suggest that the model has a good fit and explanatory capability for most constructs.

The structural model was further assessed through its ability to predict the endogenous latent variable indicators, referred to in the PLS-SEM literature as cross-validated redundancy measures (Jöreskog and Wold, 1982). This involved examining the Stone-Geisser Q2 values (Geisser, 1975; Stone, 1974) and the predominant measure of predictive relevance using blindfolding procedures (Tenenhaus et al., 2005). The Q2 values for PU, PEOU, PSE, and BI were 0.274, 0.305, 0.244, and 0.352, respectively. Q2 values above 0.35 indicate substantial predictive relevance for explaining the variable studied (Henseler et al., 2009). These positive Q2 values indicate that the model has predictive relevance for the endogenous constructs, supporting the model's robustness and validity. Overall, the R2 and Q2 results, which are the explained variances and predictive relevance, affirm the model's homological validity, demonstrating that the constructs are adequately explained by the hypothesized relationships. This indicates that the model is both theoretically adequate and empirically supported, providing a reliable framework for understanding the relationships between the constructs.

***Table 6: Inner Model Validity.***

| | $R^2$ | Cross-redundancy ($Q^2$) |
|---|---|---|
| Perceived Usefulness (PU) | 0.529 | 0.274 |
| Perceived Ease of Use (PEOU) | 0.502 | 0.305 |
| Perceived Self-Efficacy (PSE) | 0.257 | 0.244 |
| Behavioral Intention (BI) | 0.525 | 0.352 |

## 6. PLS ESTIMATES AND HYPOTHESES TESTING

The PLS path estimates for the inner model indicate that most hypotheses were supported, except for the direct effects of PT on PEOU, PU, and BI, as shown by the dashed lines in Figure 2. Notably,

PEOU and PSE exhibit significant direct and indirect effects on BI, consistent with the TAM.

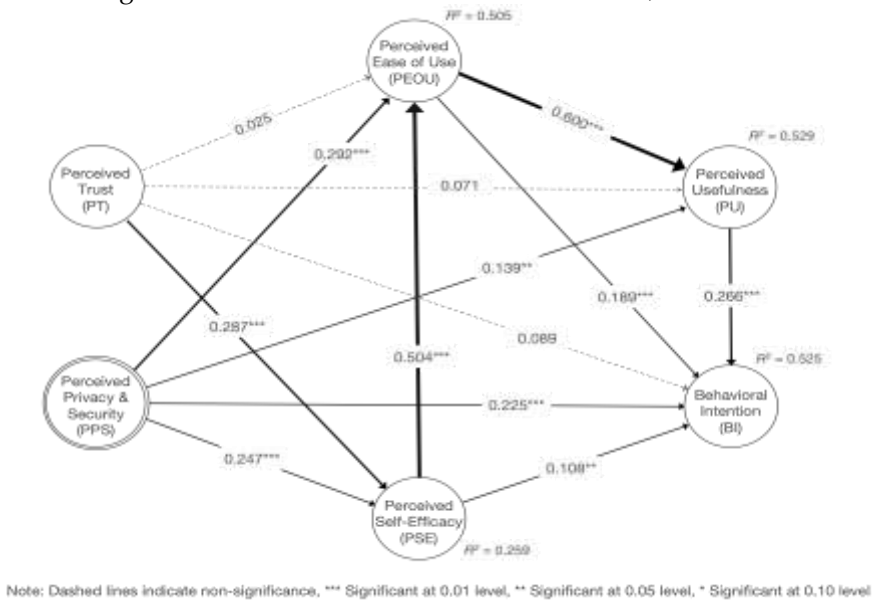


***Figure 2: PLS Results of the Structural Model.***

PEOU substantially influences PU ($\beta = 0.600$, $p < 0.01$) and BI ($\beta = 0.189$, $p < 0.01$), and it indirectly affects BI through PU ($\beta = 0.266$, $p < 0.01$). Similarly, PSE significantly impacts PEOU ($\beta = 0.504$, $p < 0.01$) and indirectly shapes BI via PEOU and PU.

The model's R2 values for PU (0.529), PEOU (0.505), PSE (0.259), and BI (0.525) demonstrate a substantial explanation of variance, underscoring the model's robustness. The solid lines in the figure highlight key relationships: the pivotal role of PEOU in enhancing PU and driving BI, and the importance of PSE in influencing PEOU.

These findings collectively validate the model's theoretical framework, confirming that PEOU and self-efficacy are critical determinants of BI, mediated through PU. This comparative analysis emphasizes the interconnectedness and relative strengths of the model's constructs in predicting user acceptance and intention.

Table 7 summarizes the direct, indirect, and total effects among various constructs. PU has the most significant, direct effect on BI. However, when both direct and indirect effects are considered, PPS exerts the highest total effect on BI, followed by PEOU and PSE. This indicates that while PU directly influences BI the most, the overall impact of PPS is greater when considering its indirect effects, highlighting the critical role of privacy and security in shaping user intentions (Gefen et al., 2003; Pavlou, 2003).

***Table 7: Standardized Direct and Indirect Effects of the Structural Model.***

| Path | | | Direct Effect | Indirect Effect | Total Effect |
|---|---|---|---|---|---|
| Perceived Usefulness | -> | Behavioral Intention | 0.266 | - | **0.266** |
| Perceived Ease-of-Use | -> | Behavioral Intention | 0.189 | 0.160 | **0.349** |
| Perceived Self-Efficacy | -> | Behavioral Intention | 0.108 | 0.176 | **0.284** |
| Perceived Trust | -> | Behavioral Intention | 0.089* | 0.109 | **0.198** |
| Perceived Privacy & Security | -> | Behavioral Intention | 0.225 | 0.207 | **0.432** |
| Perceived Ease-of-Use | -> | Perceived Usefulness | 0.600 | - | **0.600** |
| Perceived Self-Efficacy | -> | Perceived Usefulness | | 0.302 | **0.302** |
| Perceived Trust | -> | Perceived Usefulness | 0.071* | 0.101 | **0.172** |
| Perceived Privacy & Security | -> | Perceived Usefulness | 0.133 | 0.250 | **0.383** |
| Perceived Self-Efficacy | -> | Perceived Ease-of-Use | 0.504 | - | **0.504** |
| Perceived Trust | -> | Perceived Ease-of-Use | 0.025* | 0.144 | **0.169** |
| Perceived Privacy & Security | -> | Perceived Ease-of-Use | 0.292 | 0.124 | **0.417** |
| Perceived Trust | -> | Perceived Self-Efficacy | 0.287 | - | **0.287** |
| Perceived Privacy & Security | -> | Perceived Self-Efficacy | 0.247 | - | **0.247** |

Note: * indicates statistically insignificant path

Additionally, PEOU significantly influences PU, indicating that a user-friendly system enhances the

perceived value and functionality, which is crucial for user adoption (Davis, 1989). PSE impacts PEOU, suggesting that users' confidence in their abilities can shape their perceptions of system accessibility (Bandura, 1986). Both PEOU and PSE indirectly influence BI through PU, emphasizing their roles in driving user acceptance and engagement with the technology (Venkatesh and Davis, 2000).

Furthermore, PT indirectly affects BI through its influence on PU and PPS, despite its direct effects not being significant. Rather, the results suggest that PT exerts its impact primarily through mediated pathways—most notably via PPS, PU, and PEOU—which then shape behavioral intention. This aligns with studies in other financial technology contexts where trust influences adoption indirectly by first enhancing perceptions of security and utility. Given the cross-sectional design, it is also possible that trust effects require more prolonged exposure to the platform to emerge as direct behavioral drivers. This underscores the importance of fostering trust and ensuring robust privacy and security measures to enhance overall user acceptance (Gefen et al., 2003). The interconnectedness of trust, privacy, and security with other constructs highlights their critical role in shaping user behavior and intention. This indicates that while usability and self-efficacy are vital for business, building trust and ensuring security can significantly enhance user engagement and adoption rates (Pavlou, 2003).

### *6.1. Moderating Role of Financial Literacy (High vs Low financial literacy)*

The moderating role of financial literacy in the model is illustrated in Figure 3, which compares high and low financial literacy groups. The analysis reveals distinct differences in the relationships among constructs depending on the level of financial literacy.

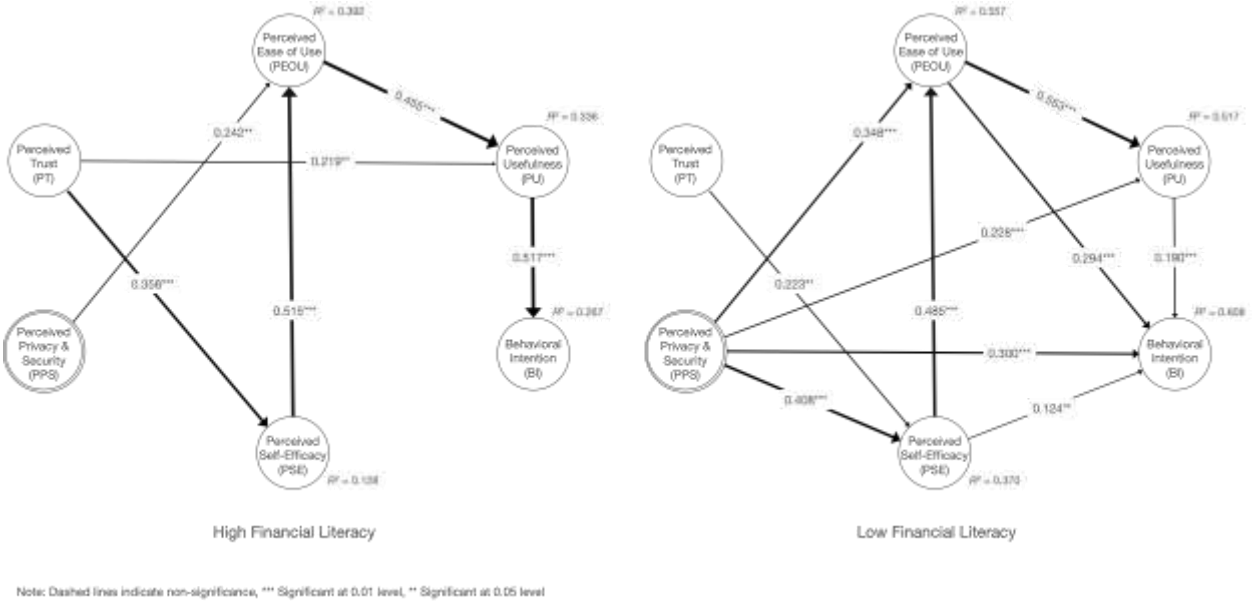


***Figure 3: Moderating Role of Financial Literacy.***

For users with high financial literacy, only PU significantly impacts BI ($\beta = 0.517$, $p < 0.05$). Both PSE and PEOU exert substantial indirect effects on BI, underscoring the critical roles of usability and self-efficacy. Furthermore, PT significantly influences both PSE ($\beta = 0.358$, $p < 0.05$) and PU ($\beta = 0.219$, $p < 0.05$), highlighting the importance of trust in enhancing perceived utility (Davis, 1989; Gefen et al., 2003).

Conversely, users with low financial literacy exhibit a more complex set of relationships. All factors, except PT, directly affects BI. PT significantly impacts PU ($\beta = 0.219$, $p < 0.05$) and PSE ($\beta = 0.358$, $p < 0.05$), indicating that trust is crucial for this group. Additionally, PPS significantly affects PEOU ($\beta = 0.242$, $p < 0.05$), emphasizing the critical nature of privacy and security concerns (Pavlou, 2003).

These findings suggest that enhancing usability and security is crucial for users with high financial literacy. Conversely, building trust and addressing security concerns are essential for engaging users with low financial literacy. This nuanced understanding can inform targeted strategies to improve user adoption and engagement across different financial literacy levels (Venkatesh and Davis, 2000). Table 8 illustrates the direct, indirect,

and total effects of various paths in the model, comparing high and low financial literacy groups.

*Table 8: Comparing between High and Low Financial Literacy Groups.*

| Path | | | High Financial Literacy | | | Low Financial Literacy | | | Differences | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Direct | Indirect | **Total** | Direct | Indirect | **Total** | Direct | Indirect | **Total** |
| PU | -> | BI | 0.435 | - | **0.435** | 0.189 | - | **0.189** | 0.246 | - | **0.246** |
| PEOU | -> | BI | 0.100$^{+}$ | 0.197 | **0.297** | 0.291 | 0.104 | **0.395** | -0.191 | 0.093 | **-0.098** |
| PSE | -> | BI | - 0.104$^{+}$ | 0.149 | 0.045$^{+}$ | 0.109 | 0.190 | **0.299** | -0.213 | -0.041 | **-0.254** |
| PT | -> | BI | 0.067$^{+}$ | 0.125$^{+}$ | 0.191$^{+}$ | 0.159$^{+}$ | 0.087 | **0.246** | -0.092 | 0.038 | **-0.055** |
| PPS | -> | BI | 0.165$^{+}$ | 0.071$^{+}$ | 0.236$^{+}$ | 0.178 | 0.286 | **0.464** | -0.013 | -0.215 | **-0.228** |
| PEOU | -> | PU | 0.452 | - | **0.452** | 0.549 | - | **0.549** | -0.097 | - | **-0.097** |
| PSE | -> | PU | - | 0.226 | **0.226** | - | 0.265 | **0.265** | - | -0.039 | **-0.039** |
| PT | -> | PU | 0.188$^{+}$ | 0.122$^{+}$ | **0.310** | 0.047$^{+}$ | 0.075$^{+}$ | 0.122$^{+}$ | 0.141 | 0.047 | **0.188** |
| PPS | -> | PU | 0.042$^{+}$ | 0.080 | 0.121$^{+}$ | 0.190 | 0.286 | **0.477** | -0.148 | -0.206 | **-0.356** |
| PSE | -> | PEOU | 0.501 | - | **0.501** | 0.482 | - | **0.482** | 0.019 | - | **0.019** |
| PT | -> | PEOU | 0.089$^{+}$ | 0.180 | **0.269** | 0.030$^{+}$ | 0.107 | 0.137$^{+}$ | 0.059 | 0.073 | **0.132** |
| PPS | -> | PEOU | 0.177$^{+}$ | - 0.001$^{+}$ | 0.176$^{+}$ | 0.325 | 0.197 | **0.521** | -0.148 | -0.198 | **-0.345** |
| PT | -> | PSE | 0.360 | - | **0.360** | 0.223 | - | **0.223** | 0.137 | - | **0.137** |
| PPS | -> | PSE | - 0.002$^{+}$ | - | - 0.002$^{+}$ | 0.408 | - | **0.408** | -0.410 | - | **-0.410** |

Note: $^{+}$ indicates statistically insignificant path

For users with high financial literacy, PU has a substantial direct effect on BI (β = 0.435), indicating that these users prioritize the usefulness of digital lending platforms (Davis, 1989). Conversely, PU has a lower direct effect on BI in the low financial literacy group (β = 0.189). PEOU is crucial for users with lower financial literacy, with a significant direct effect on BI (β = 0.291), unlike in the high financial literacy group where it is insignificant (β = 0.100) (Venkatesh and Davis, 2000). PSE positively affects BI in the low financial literacy group (β = 0.109) but negatively and insignificantly affects the high financial literacy group (β = -0.104). PT and PPS have higher direct effects on BI in the low financial literacy group (PT: β = 0.159, PPS: β = 0.178), highlighting their importance (Gefen et al., 2003; Pavlou, 2003).

Regarding indirect effects, PU has no indirect effects on BI. PEOU's indirect effect on BI is stronger in the high financial literacy group (β = 0.197) than in the low financial literacy group (β = 0.104). PSE's indirect effect on BI is more significant in the low financial literacy group (β = 0.190) compared to the high financial literacy group (β = 0.149). PT's indirect effects are higher in the high financial literacy group (β = 0.125), and PPS's indirect effects are significant only in the low financial literacy group (β = 0.286).

The total effect of PU on BI is higher in the high financial literacy group (β = 0.435) compared to the low financial literacy group (β = 0.189), indicating its critical role for knowledgeable users (Davis, 1989). PEOU's total effect on BI is higher in the low financial literacy group (β = 0.395) than in the high financial literacy group (β = 0.297), underscoring its significance for less knowledgeable users. The total effect of PSE on BI is much higher in the low financial literacy group (β = 0.299) than in the high financial literacy group (β = 0.045), highlighting the importance of self-efficacy for less financially literate users. PT's total effect on BI is higher in the low financial literacy group (β = 0.246) compared to the high financial literacy group (β = 0.191). PPS has a higher total effect on BI in the low financial literacy group (β = 0.464) than in the high financial literacy group (β = 0.236) (Gefen et al., 2003; Pavlou, 2003).

In summary, for users with high financial literacy, PU is the most critical driver of BI. Conversely, for users with low financial literacy, PEOU, PSE, and PPS are more significant. Businesses should tailor strategies based on financial literacy, focusing on ease of use, self-efficacy, and privacy or security for less financially literate users, and emphasizing the usefulness of the platform for more knowledgeable

users.

### *6.2. Moderating Role of Income Level (High vs Low Income)*

The moderating role of income level reveals critical differences between high- and low-income groups, as shown in Figure 4 and Table 9. For high-income users, PU has the most substantial direct impact on BI (β = 0.257). PEOU also significantly impacts BI directly (β = 0.232) and indirectly (β = 0.134), totaling (β = 0.367). PSE has a strong indirect impact on BI (β = 0.169), bringing the total to (β = 0.301), despite its direct effect being insignificant. PPS exerts a significant direct (β = 0.237) and indirect impact (β = 0.188), totaling 0.425.

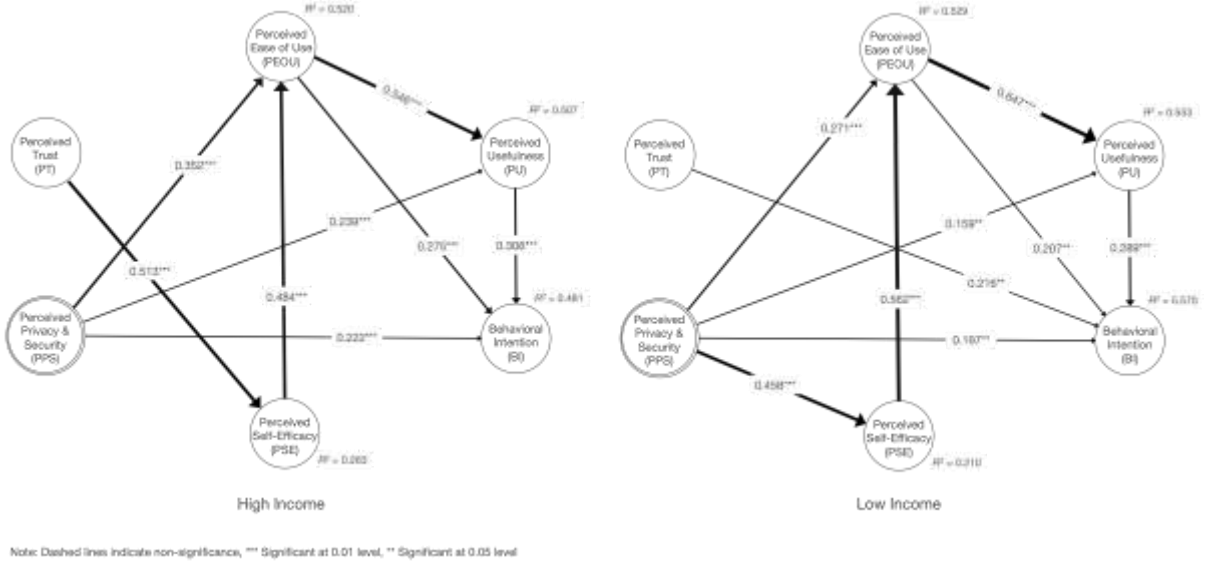


*Figure 4: Moderating Role of Income Level.*

Conversely, for low-income users, multiple factors, including PU (β = 0.273), PEOU (direct: β = 0.147; indirect: β = 0.176, total: β = 0.324), and PPS (direct: β = 0.202; indirect: β = 0.225, total: β = 0.427), directly affects BI. Additionally, PT significantly impacts BI indirectly (total: β = 0.246), despite its direct path being insignificant.

Table 9 further elucidates these relationships. For the high-income group, the direct effect of PEOU on PU is substantial (β = 0.523), whereas this effect is even stronger in the low-income group (β = 0.647). This implies that enhancing ease of use is crucial for both groups but has a more significant impact on PU for low-income users (Venkatesh and Davis, 2000).

***Table 9: Comparing between High and Low Income Groups.***

| | | | High Income | | | Low Income | | | Differences | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Path** | | | Direct | Indirect | **Total** | Direct | Indirect | **Total** | Direct | Indirect | **Total** |
| PU | -> | BI | 0.257 | - | **0.257** | 0.273 | - | **0.273** | -0.016 | - | -0.016* |
| PEOU | -> | BI | 0.232 | 0.134 | **0.367** | 0.147* | 0.176 | **0.324** | 0.085 | -0.042 | 0.043* |
| PSE | -> | BI | 0.132* | 0.169 | **0.301** | 0.116* | 0.183 | **0.300** | 0.016 | -0.014 | 0.001* |
| PT | -> | BI | -0.032* | 0.194 | 0.162* | 0.195 | 0.050* | **0.246** | -0.227 | 0.144 | -0.084* |
| PPS | -> | BI | 0.237 | 0.188 | **0.425** | 0.202 | 0.225 | **0.427** | 0.035 | -0.037 | -0.002* |
| PEOU | -> | PU | 0.523 | - | **0.523** | 0.647 | - | **0.647** | -0.124 | - | -0.124* |
| PSE | -> | PU | - | 0.240 | **0.240** | - | 0.366 | **0.366** | - | -0.126 | -0.126* |
| PT | -> | PU | 0.135* | 0.157 | **0.293** | 0.025* | 0.037* | 0.062* | 0.110 | 0.120 | **0.231** |
| PPS | -> | PU | 0.145 | 0.179 | **0.325** | 0.138* | 0.310 | **0.448** | 0.007 | -0.131 | -0.123* |
| PSE | -> | PEOU | 0.460 | - | **0.460** | 0.566 | - | **0.566** | -0.106 | - | -0.106* |
| PT | -> | PEOU | 0.133* | 0.169 | **0.301** | -0.066* | 0.122* | 0.057* | 0.199 | 0.047 | **0.244** |
| PPS | -> | PEOU | 0.259 | 0.085* | **0.343** | 0.325 | 0.155 | **0.480** | -0.066 | -0.070 | -0.137* |
| PT | -> | PSE | 0.367 | - | **0.367** | 0.216* | - | **0.216*** | 0.151 | - | 0.151* |
| PPS | -> | PSE | 0.184* | - | 0.184* | 0.274 | - | **0.274** | -0.090 | - | -0.090* |

Note: * indicates statistically insignificant path

PT has a notable impact on PEOU (β = 0.301) and PU (β = 0.293) in the high-income group, indicating

that trust mechanisms must be robust for these users (Gefen et al., 2003). In the low-income group, PT's influence on PEOU (β = 0.057) and PU (β = 0.062) is less pronounced, suggesting that other factors may play a more critical role.

PPS significantly influences BI in both income groups, with a slight edge in the low-income group (high-income: β = 0.425; low-income: β = 0.427), underscoring the importance of privacy and security (Pavlou, 2003).

Self-efficacy (PSE) impacts PEOU significantly in both groups (high-income: β = 0.460; low-income: β = 0.566) and indirectly influences PU (high-income: β = 0.240; low-income: β = 0.366). This indicates that self-efficacy is a crucial driver for PEOU and usefulness in the low-income group, highlighting the importance of confidence-building measures for these users (Bandura, 1986).

These findings suggest that for high-income users, enhancing usability and security directly drives PU and subsequently, BI. For low-income users, building trust and addressing privacy and security concerns are essential for engagement. This nuanced understanding can guide businesses to tailor their strategies effectively to improve user adoption and engagement across different income levels (Davis, 1989; Venkatesh and Davis, 2000).

### *6.3. Co-moderating Role of Financial Literacy and Income Level*

The co-moderating effects of financial literacy and income level on the proposed model reveal distinct patterns across four groups: low financial literacy with high income, high financial literacy with high income, low financial literacy with low income, and high financial literacy with low income. Each group shows varied key factors that most significantly impact BI, as highlighted in Figure 5.

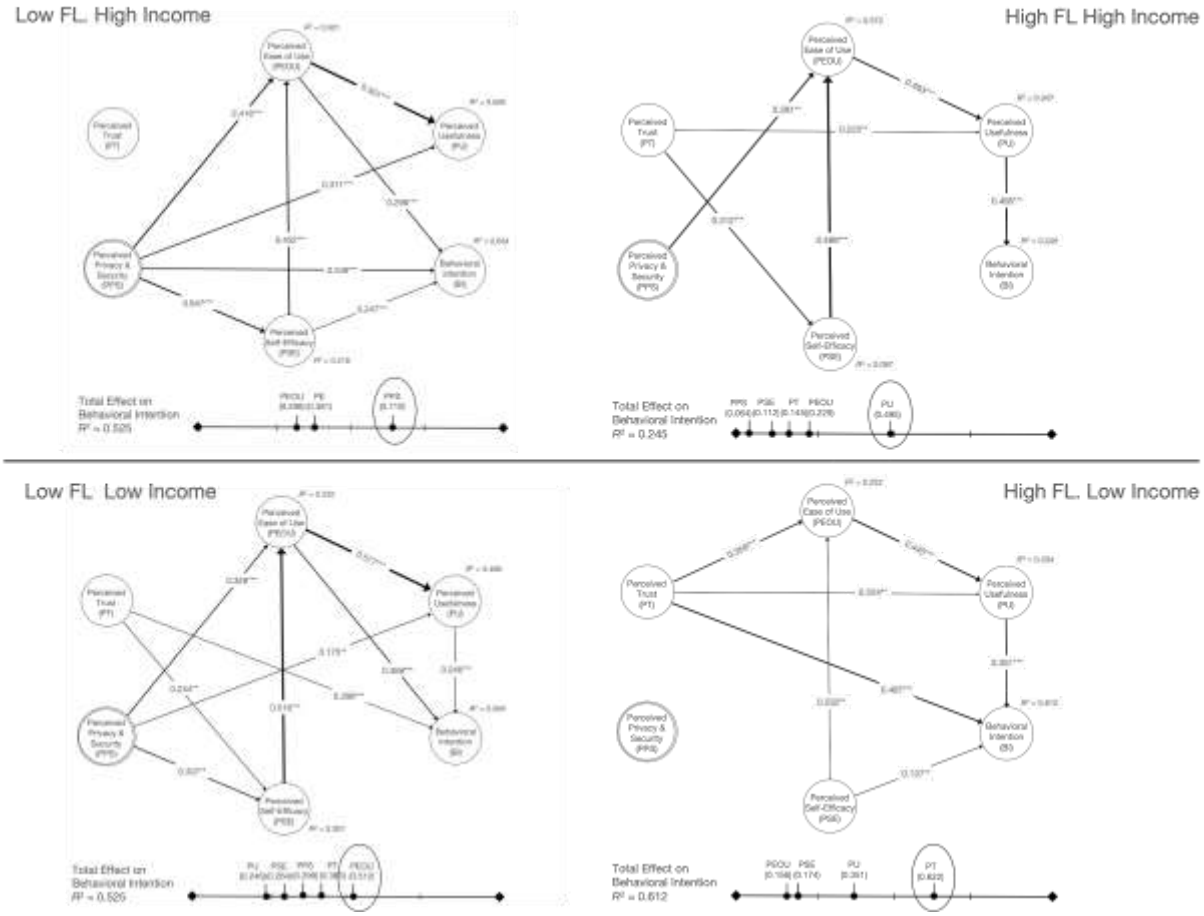


*Figure 5: Co-moderating Role of Financial Literacy and Income Level.*

**Low Financial Literacy, High Income (Top Left):** In this group, PPS has the highest total effect on BI. Users with low financial literacy but high income are primarily concerned with privacy and security, indicating that they need assurance that their data is safe and secure. This demographic may adopt new technologies when confident about their privacy and security (Pavlou, 2003).

**High Financial Literacy, High Income (Top Right):** For this group, PU has the highest total effect on BI. High-income users with high financial literacy prioritize the benefits and practical advantages of the system. This suggests that demonstrating the utility and effectiveness of the technology is crucial for engaging these users (Davis, 1989). According to Davis's TAM, PU is a fundamental determinant of user acceptance, which aligns with the findings in this group.

**Low Financial Literacy, Low Income (Bottom Left):** In this group, PEOU is a crucial factor with the highest total effect on BI. Users with low financial literacy and low income prioritize the ease of use of the system. Improving the user experience and making the system more accessible can significantly encourage adoption in this group (Venkatesh and Davis, 2000). This aligns with Venkatesh and Davis's extended TAM, which highlights the importance of ease of use in technology acceptance.

**High Financial Literacy, Low Income (Bottom Right):** In this group, PT is the most influential factor on BI. Low-income users with high financial literacy require trust in the technology before adoption. Building substantial trust through transparent practices, reliable performance, and trustworthy endorsements is essential for engaging these users (Gefen et al., 2003). Gefen et al. (2003) demonstrated that trust significantly influences technology acceptance, which is evident in this group's findings.

## 7. CONCLUSION

This study of BI towards digital lending platforms reveals several key drivers and mediating factors. The main determinants are PU, PEOU, PPS, and PT. PU is a significant predictor, indicating that users may likely adopt digital lending if they perceive it as beneficial and efficient (Davis, 1989). PEOU enhances BI by making the platform user-friendly (Venkatesh and Davis, 2000). PPS and PT are also crucial, as users require assurance that their data is secure and the platform can be trusted (Gefen et al., 2003; Pavlou, 2003).

The moderating effects of financial literacy and income level reveal distinct patterns. High-income users with high financial literacy prioritize PU, reflecting the importance of perceived benefits. Conversely, high-income users with low financial literacy are most concerned with PPS. Low-income users with low financial literacy focus on PEOU, highlighting the need for an easy-to-use interface. For low-income users with high financial literacy, PT becomes the most significant factor, indicating a substantial need for trust in the technology (Davis, 1989; Gefen et al., 2003; Pavlou, 2003; Venkatesh and Davis, 2000).

The co-moderating effects further clarify these preferences. Users with low financial literacy and high income prioritize PPS, while those with high financial literacy and high income emphasize PU. Low-income users with low financial literacy focus on PEOU, and those with high financial literacy stress PT. These insights suggest that businesses should tailor their strategies to address specific concerns and needs across different financial literacy and income levels, enhancing user adoption and engagement with digital lending platforms (Davis, 1989; Gefen et al., 2003; Pavlou, 2003; Venkatesh and Davis, 2000).

### *7.1. Business Implication*

The primary drivers of BI towards digital lending platforms are PU, PEOU, PPS, and PT. Businesses should focus on enhancing the perceived benefits of their digital lending services by emphasizing efficiency and utility (Davis, 1989). Improving usability is crucial; a user-friendly interface can significantly boost adoption (Venkatesh and Davis, 2000). Ensuring robust privacy and security measures builds user confidence and trust, critical for engagement and retention (Gefen et al., 2003; Pavlou, 2003).

Financial literacy and income level moderate the impact of these drivers on BI. For high-income users with high financial literacy, highlighting the practical benefits of digital lending platforms is crucial (Davis, 1989). High-income users with low financial literacy emphasize PPS, necessitating robust security features (Pavlou, 2003). Low-income users with low financial literacy prioritize ease of use, making intuitive, user-friendly designs and onboarding processes crucial (Venkatesh and Davis, 2000). For low-income users with high financial literacy, building and maintaining trust through transparent practices and reliable performance is essential (Gefen et al., 2003). These findings align with Boonlertvanich's (2018) study, which emphasizes that trust and perceived service quality are critical for customer loyalty, particularly across different wealth levels.

In **addition to the general implications above, co-moderating effect, analysis helps provide deeper segment-specific strategies as follow**

- High-income, high-literacy users: Key influence construct is Perceived Usefulness (PU), suggesting businesses should demonstrate the practical benefits and efficiency of their platforms, such as emphasizing advanced functionalities,

personalized loan products, and efficiency gains (Davis, 1989). Digital lender can also communicate comparative advantages over traditional lending with data-driven evidence.

- High-income, low-literacy users: Key influence construct is Perceived Privacy and Security (PPS), indicating a need for significant privacy and security assurances. Digital lender should focus on building confidence in data privacy and security, implementing visible security features (e.g., biometric authentication, encryption notices) and using plain-language explanations.
- Low-income, low-literacy users: Ease of use remains paramount, necessitating simplified user interfaces (Venkatesh and Davis, 2000). Digital lender should seek to provide simplified onboarding with step-by-step guidance, intuitive navigation, and visual aids. In addition, offering assisted application options via community agents or branch kiosks should also be considered.
- Low-income, high-literacy users: They prioritize trust, requiring transparent communication and reliable endorsements (Gefen et al., 2003). As a result, transparent communication of terms, consistent service reliability, and endorsements from trusted institutions or consumer advocates are key success factors for this segment.

**For regulators and policymakers, initiatives could include**

- Launching targeted financial literacy campaigns aligned with digital credit product rollouts.
- Establishing minimum security and privacy certification standards for digital lenders.
- Providing incentives for lenders to develop inclusive design features that accommodate low-literacy and low-income segments.

### *7.2. Limitations and Future Research*

This study was analyzed based on single-country data, thus future research using multi-country data could help generalized the research results. In addition, this study was conducted based on a cross-sectional data, a longitudinal analysis to assess causality and time-dependent impacts would sharpen our research results, e.g., perceived trust might take longer time to affect behavioral intention. The data in this study were obtained from customers of a large commercial bank; another study on customers of non-bank lending institution or FinTech could be conducted to confirm our results. Finally, key product features such as interest rate, payment term, associated fees, etc., might also impact customers' adoption behavior. Therefore, adding product features into the proposed model would be another key area for future study.

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## APPENDIX

*Table A1: Demographics of the Sample.*

| Demographics | Number | Percentage |
|---|---|---|
| *Sex* | | |
| Male | 260 | 58.0 |
| Female | 187 | 41.7 |
| *Age (years)* | | |
| Millennials or younger | 265 | 59.2 |
| Gen-X or older (42 years old or older) | 183 | 40.8 |
| *Marital status* | | |
| Single | 166 | 37.1 |
| Married | 134 | 29.9 |
| Divorced/Widowed/Separated | 14 | 3.1 |
| *Education attainment* | | |
| High school or lower | 108 | 24.1 |
| Diploma | 81 | 18.1 |
| Bachelor degree | 237 | 52.9 |
| Postgraduate | 22 | 4.9 |
| *Type of occupation* | | |
| Salary earner | 402 | 89.7 |
| Self-employed | 43 | 9.6 |
| *Income range (Baht/month)* | | |
| Less than 20,000 | 122 | 27.2 |
| 20,000 - 30,000 | 113 | 25.2 |
| 30,000 - 50,000 | 121 | 27.0 |
| 50,000 - 100,000 | 60 | 13.4 |
| More than 100,000 | 32 | 7.1 |
| *Debt-to-Monthly Income* | | |
| Less than 35 | 109 | 24.3 |
| 35 - 50 | 59 | 13.2 |
| 50 - 65 | 66 | 14.7 |
| More than 65 | 80 | 17.9 |

* some of the samples did not answer some question so the total count of some question is less than 448

*Table A2: Financial Product Holding and Borrowing Channel.*

| Financial Products and Borrowing Experience | Number | Percentage |
|---|---|---|
| *Financial Product Holding* | | |
| Saving Account | 55 | 12.3 |
| Mutual Fund | 178 | 39.7 |
| Bancassurance | 315 | 70.3 |
| Creditcard | 81 | 18.1 |
| Personal Loan | 101 | 22.5 |
| Home Loan | 86 | 19.2 |
| *Number of Financial Product Holding* | | |
| 0 product | 30 | 6.7 |
| 1 product | 182 | 40.6 |
| 2 products | 130 | 29.0 |
| 3 products | 68 | 15.2 |
| 4 products | 20 | 4.5 |
| 5 products | 18 | 4.0 |
| *Borrowing Experience* | | |
| Physical / Branch channel | 119 | 26.6 |
| Digital channel - drop lead | 135 | 30.1 |
| Digital channel - applied | 194 | 43.3 |

*Table A3: Financial and Debt Literacy.*

| | Financial Literacy Assessment Questions | Answer Choices |
|---|---|---|
| 1 | Interest Calculation: Suppose you have 100 baht in a savings account and the interest rate is 2% per year. After 5 years, how much money do you think you will have in the account if you leave the money without making additional deposits? | A. > 102 Baht<br>B. = 102 Baht<br>C. < 102 Baht |
| 2 | Inflation: Imagine that the interest rate on your savings account is 1% per year and the inflation rate is 2% per year. After 1 year, how much value will the money in this account be able to buy? | A. > value of money today<br>B. = value of money toay<br>C. < value of money today |
| 3 | Diversification: Buying stock from a single company usually provides safer returns than an equity mutual fund. | A. Right<br>B. Wrong<br>C. Don't know |

| Financial Literacy | Number | Percentage |
|---|---|---|
| *Financial Literacy* | | |
| 0 point | 145 | 32.4 |
| 1 point | 144 | 32.1 |
| 2 points | 75 | 16.7 |
| 3 points | 29 | 6.5 |
| N/A | 55 | 12.3 |

*Table A4: Constructs' Items.*

| Construct | Items | Mean | SD |
|---|---|---|---|
| Perceived Usefulness (PU) | | | |
| PU1 | I believe that digital personal loans will facilitate faster access to credit. | 4.359 | 0.979 |
| PU2 | I believe that digital personal loans will enable me to obtain the specific loans I require. | 3.362 | 0.979 |
| Perceived Ease-of-Use (PEOU) | | | |
| PEOU1 | I believe that applying for digital personal loans is very easy. | 4.406 | 0.926 |
| PEOU2 | I believe that applying for digital personal loans requires no effort. | 4.406 | 0.926 |
| PEOU3 | I believe that the process of applying for digital personal loans is easy to understand and straightforward. | 4.408 | 0.931 |
| PEOU4 | I believe that applying for digital personal loans is a simple way to obtain credit. | 4.413 | 0.927 |
| PEOU5 | I believe that I can apply for digital personal loans on my own. | 4.420 | 0.917 |
| Perceived Self-Efficacy (PSE) | | | |
| PSE1 | I can apply for digital personal loans on my own even without someone guiding me through the process. | 4.279 | 0.991 |
| PSE2 | I can apply for digital personal loans on my own even if I have never done it before. | 4.286 | 0.988 |
| PSE3 | I can apply for digital personal loans on my own if there is a help function during the application process. | 4.317 | 0.941 |
| PSE4 | I can apply for digital personal loans on my own if someone demonstrates it to me first. | 4.290 | 0.959 |
| PSE5 | I can apply for digital personal loans on my own if I can call for help when I encounter a step I cannot complete. | 4.315 | 0.943 |
| Perceived Trust (PT) | | | |
| PT1 | I believe that digital personal loans are reliable. | 4.181 | 1.003 |
| PT2 | I believe that digital personal loans maintain data confidentiality | 4.174 | 1.003 |
| PT3 | I believe that once the application for digital personal loans is completed, I will receive immediate confirmation of the application. | 4.176 | 1.013 |
| PT4 | I expect that digital personal loans will be a trustworthy service. | 4.174 | 1.014 |
| Perceived Privacy & Security (PPS) | | | |
| *Perceived Privacy (PP)* | | | |
| PP1 | I believe that digital personal loans will not invade my privacy. | 4.167 | 1.033 |
| PP2 | I believe that digital personal loans protect my privacy very well. | 4.163 | 1.036 |
| PP3 | I believe that digital personal loans will not cause my personal information to be leaked. | 4.165 | 1.033 |
| PP4 | I believe that digital personal loans will not make me worry about my privacy. | 4.165 | 1.035 |
| *Perceived Security (PS)* | | | |
| PS1 | I believe that digital personal loans can be safely assessed. | 4.243 | 0.971 |
| PS2 | I believe that digital personal loans will confirm my loan application. | 4.243 | 0.971 |
| PS3 | I believe that digital personal loans are financially secure. | 4.250 | 0.973 |
| PS4 | Overall, I am not concerned about the safety of applying for digital personal loans. | 4.252 | 0.973 |
| Behavioral Intention (BI) | | | |
| BI1 | I intend to apply for personal loans through digital personal loans in the future. | 4.417 | 0.990 |
| BI2 | I intend to use digital personal loans as my first choice instead of applying for loans through bank branches. | 4.440 | 0.989 |
| BI3 | I plan to use digital personal loans whenever I need a personal loan. | 4.435 | 0.982 |
| BI4 | I believe that I will use digital personal loans again in the future. | 4.438 | 0.980 |

*Table A5: Cross-loadings of Outer Model.*

| | PP | PS | PU | PEOU | PSE | PT | BI |
|---|---|---|---|---|---|---|---|
| PP1 | ***1.000*** | 0.818 | 0.469 | 0.493 | 0.436 | 0.828 | 0.545 |
| PP2 | ***0.998*** | 0.814 | 0.469 | 0.492 | 0.432 | 0.825 | 0.543 |
| PP3 | ***1.000*** | 0.818 | 0.468 | 0.493 | 0.434 | 0.828 | 0.544 |
| PP4 | ***0.998*** | 0.817 | 0.467 | 0.492 | 0.433 | 0.826 | 0.542 |
| PS1 | 0.818 | **0.998** | 0.530 | 0.565 | 0.481 | 0.733 | 0.587 |
| PS2 | 0.816 | **0.998** | 0.525 | 0.562 | 0.480 | 0.732 | 0.589 |
| PS3 | 0.817 | **0.999** | 0.529 | 0.565 | 0.484 | 0.733 | 0.588 |
| PS4 | 0.816 | **0.999** | 0.523 | 0.558 | 0.482 | 0.731 | 0.580 |
| PU1 | 0.470 | 0.528 | ***1.000*** | 0.710 | 0.611 | 0.486 | 0.628 |
| PU2 | 0.467 | 0.527 | ***1.000*** | 0.709 | 0.611 | 0.483 | 0.626 |
| PEOU1 | 0.492 | 0.558 | 0.708 | ***0.995*** | 0.649 | 0.501 | 0.609 |
| PEOU2 | 0.493 | 0.563 | 0.710 | ***0.997*** | 0.653 | 0.510 | 0.619 |
| PEOU3 | 0.490 | 0.558 | 0.711 | ***0.998*** | 0.653 | 0.507 | 0.621 |
| PEOU4 | 0.487 | 0.559 | 0.705 | ***0.995*** | 0.655 | 0.508 | 0.622 |
| PEOU5 | 0.492 | 0.566 | 0.699 | ***0.994*** | 0.659 | 0.511 | 0.611 |
| PSE1 | 0.455 | 0.503 | 0.637 | 0.691 | ***0.964*** | 0.501 | 0.542 |
| PSE2 | 0.448 | 0.497 | 0.632 | 0.695 | ***0.968*** | 0.496 | 0.539 |
| PSE3 | 0.403 | 0.449 | 0.554 | 0.590 | ***0.975*** | 0.460 | 0.513 |
| PSE4 | 0.396 | 0.440 | 0.571 | 0.601 | ***0.971*** | 0.451 | 0.534 |
| PSE5 | 0.400 | 0.445 | 0.561 | 0.596 | ***0.975*** | 0.458 | 0.522 |
| PT1 | 0.830 | 0.737 | 0.483 | 0.508 | 0.484 | ***0.994*** | 0.550 |
| PT2 | 0.831 | 0.733 | 0.488 | 0.511 | 0.481 | ***0.992*** | 0.547 |
| PT3 | 0.813 | 0.722 | 0.475 | 0.500 | 0.487 | ***0.994*** | 0.541 |
| PT4 | 0.813 | 0.721 | 0.480 | 0.506 | 0.488 | ***0.993*** | 0.549 |
| BI 1 | 0.539 | 0.584 | 0.603 | 0.608 | 0.538 | 0.543 | ***0.981*** |
| BI 2 | 0.542 | 0.583 | 0.627 | 0.620 | 0.550 | 0.550 | ***0.990*** |
| BI 3 | 0.535 | 0.576 | 0.638 | 0.621 | 0.542 | 0.542 | ***0.988*** |
| BI 4 | 0.533 | 0.574 | 0.608 | 0.594 | 0.528 | 0.540 | ***0.990*** |