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Drivers of Continuance Intention for Borrowing Using Digital Lending Applications: An Expectancy Confirmation Model Approach#

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Abstract

The rapid demand for credit, combined with advancements in Financial Technology (FinTech), has prompted the widespread adoption of Digital Lending Applications (DLAs), offering borrowers greater flexibility and access compared to traditional banking and microfinance services. Despite their growing popularity, concerns about high interest rates, hidden fees and usability issues may discourage continued usage. This study investigates how Perceived Cost (PC) and factors from the Expectancy Confirmation Model (ECM), including Perceived Usefulness (PU), Confirmation of Expectation (CONF) and Satisfaction (SAT), influence borrowers' intentions to continue using DLAs. A survey-based methodology was employed, with purposive sampling yielding 349 valid responses from several states in India. We analysed the collected data using Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) via IBM AMOS SPSS 23.0. The results we found show that despite perceived cost affecting user behaviour, borrowers prioritise overall platform functionality and user experience as opposed to the cost of credit services. We suggest that management of expectations is important in enhancing user satisfaction, which is key to promoting long-term engagement. These findings offer practical insights for FinTech providers seeking to improve retention and for policymakers striving to create a supportive regulatory environment for digital lending. Future research could extend this work by exploring pre-adoption behaviour, cross-cultural differences and the long-term impact of DLAs on financial well-being.

Keywords: Continuance Borrowing Intention, Credit, DLAS, DLAs, FinTech

1. Introduction

The digital lending market is growing at an incredible rate and is now projected to reach USD 20.5 billion by 2026, with a Compound Annual Growth Rate (CAGR) of 13.8% (Markets and Markets, 2021). This increase is propelled by the popular use of smartphones, increased digitalisation, an expanding demand for convenient financial solutions and the emergence of COVID-19, leading to the popularity of digital lending platforms that offer quick access to loans with minimal documentation (Glance, 2024; Agarwal, 2023; Berg *et al*., 2022; Fu & Mishra, 2021; O'Toole *et al*., 2020). The introduction of DLAs has come as a salvage to the long-looming problem of financial inclusion by offering loans to the underserved and the minority in society (Allen *et al*., 2016; Biscaye *et al*., 2017). Digital lending refers to remote and automated lending processes through seamless digital technologies in customer acquisition, credit assessment, loan approval, disbursement, recovery and associated customer service (Reserve Bank of India, 2021). When the entire lending process is app-based or purely online, it is considered digital lending (Buchak *et al*., 2018; Fuster *et al*., 2018). DLAs are mobile and web-based applications with user interfaces that facilitate borrowing by a financial consumer from a digital lender (Reserve Bank of India, 2021). Different from

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Buy Now Pay Later (BNPL)apps, DLAs in this study focus on providers of monetary credit directly to their users.

Despite the widespread adoption of DLAs, understanding the factors driving Continued Intention for Borrowing (COIN) i.e., the decision to continue using these platforms for credit needs remains underexplored in the literature. Prior research primarily focused on the initial adoption and use of various fintech solutions like mobile payments and e-commerce (Amoroso & Lim, 2017; Chuang *et al*., 2020; Foroughi *et al*., 2019; Purohit *et al*., 2022). Despite these studies offering insights into the pre-adoption and adoption phases, none of them addresses the post-adoption behaviour, which is vital for the long-term success and sustainability of financial technologies, most especially pertaining to digital lenders.

This study aims to fill in this gap by using the Expectancy Confirmation Model (ECM) to examine factors influencing the continuance intention to borrow using DLAs. The ECM theory emphasises that post-adoption intentions are shaped by Perceived Usefulness (PU), Confirmation of Expectations (CONF) and user satisfaction (Bhattacherjee, 2001b). This study has resorted to also integrating Perceived Cost (PC) in order to capture financial and non-financial sacrifices made by borrowers. Our research seeks to offer insights into DLA lending by examining these factors: CONF, PU, PC and SAT to promote borrower retention, enhance platform usability, and provide advice on different policy interventions aimed at encouraging a sustainable digital lending system.

In emergent markets like India, where the financial inclusion agenda is particularly insistent, DLAs have gained exponential increases among youngsters, and those without formal credit histories topping the list (NSFI, 2019; Yu & Zhang, 2021). It is, therefore, important to understand why borrowers continue to use these platforms for credit after their initial adoption. Therefore, factors such as PU, CONF and SAT are presumed to play a pivotal role in shaping the post-adoption decision. However, there is still no comprehensive study done to examine COIN specifically within the DLA context. This research addresses this critical gap by exploring the post-adoption behaviour of DLA users by offering valuable insights into how these platforms can promote user retention, build long-term relationships, and enhance financial inclusion. Furthermore, understanding these determinants will aid stakeholders, including app developers and policymakers, in optimising strategies to improve customer engagement and sustained platform usage.

The remaining part of the paper includes the second literature review, the third research methodology, the fourth results, the fifth discussion and finally, the sixth conclusion.

2. Literature Review

2.1 Theoretical Model

The rapid adoption of DLAs has transformed the way individuals and businesses access credit. These platforms, driven by financial technology (FinTech) innovations, have provided an alternative to traditional banking, especially for underserved populations (Cumming *et al*., 2021). As the demand for accessible and efficient borrowing solutions continues to rise, understanding the factors influencing users' continued engagement with DLAs becomes increasingly important. Existing research on digital lending primarily focuses on initial adoption and user behaviour, but there is a limited exploration of the factors that drive post-adoption behaviour, such as COIN (Bhattacherjee, 2001a; Oghuma *et al*., 2016).

According to Bhattacherjee (2001b), the ECM theory has been used to study the COIN of individuals and organizations using various information systems. Different studies have validated the suitability of ECM theory from different mobile technologies points of view like mobile payment, e-commerce, messaging apps and smartphone banking, among others (C.C & Prathap, 2020; Chou et al., 2014; Hsu & Lin, 2015; Kim, 2010; Oghuma *et al*., 2015, 2016; Susanto *et al*., 2016; Tam *et al*., 2020). This model has, however, not been used in the post-acceptance phase of DLAs to understand why borrowers want to continue using these services for their loans. Since the original ECM focussed on PU, expectation CONF, SAT, and COIN on information systems, this research will include a

keen focus on PC alongside all the ECM constructs plus an additional difference in the context to create a baseline for future studies concentrating on the behavioural studies of borrowers. The advantage of using ECM is that it allows for direct comparison between the adoption vs. the post-adoption perceptions like confirmation vs. disconfirmation, as well as satisfaction vs. dissatisfaction with the use of a particular technological service (Bhattacherjee, 2001b).

2.2 Hypothesis Formulation

2.2.1 Confirmation of Expectations (CONF)

Refers to an incidence where the service from borrowing using DLAs meets the expectations of the borrowers (Bhattacherjee, 2001b). Through previous use or from information gathered around peers or online, people tend to develop different expectations about different services. When their expectations are met, it is a confirmation. The initial information is obtained from advertisements, personal research and news all over about the DLAs. CONF is formed in the borrower's mind psychologically as a comparison of their expectations from pre-formed judgment and their experiences. This determines whether their cognitive judgment is negative or positive opinion. Prior research has demonstrated that CONF plays a critical role in shaping users' PU and SAT (Hong *et al*., 2006). DLAs provide different utilities that a person can expect. CONF is also believed to have a positive influence on PU. This leads to our two hypotheses:

H1: Confirmation of expectations has a positive influence on satisfaction of borrowing using DLAs.

H2: Confirmation of expectations has a positive influence on the perceived usefulness of DLAs.

2.2.2 Perceived Usefulness (PU)

Refers to the recognition of the benefits that arise from using a particular information system. According to the Technology Acceptance Model (TAM), PU is captured as having a direct influence on behavioural intention (Davis *et al*., 1989). Borrowers will continue borrowing using DLAs if only they consider the means useful for them. Anything perceived is opposite to that which is objective and hence tends to vary depending on the attitude of the individual (Ajzen, 1991). Similarly, according to ECM, PU has a direct impact on COIN for borrowing as well as SAT. SAT only arises when an individual is able to derive certain use from the goods or otherwise services they are outsourcing from certain technologies. PU has shown persistent results during both pre- and post-adoption of different information systems (Effendy *et al*., 2021; Foroughi *et al*., 2019; Hong *et al*., 2006; Okine *et al*., 2023).

H3: Perceived usefulness has a positive influence on the satisfaction derived from using DLAs

H4: Perceived usefulness has a positive influence on continuance intention to borrow using DLAs.

2.2.3 Perceived Cost (PC)

Represents the financial and non-financial sacrifices a user makes when using a service, including transaction fees, time and effort (B. Fu *et al*., 2013; Soane *et al*., 2010). In the context of DLAs, PC could involve concerns about high interest rates, hidden fees, or burdensome repayment terms, which may reduce user intention to continue borrowing (Maryam Eftekhari *et al*., 2015; Özbek *et al*., 2015). Studies have shown that perceived transactional cost has a negative influence on COIN to use fintech (Zhao *et al*., 2024). Several studies have shown that higher PCs lead to dissatisfaction and reduce the intention to continue using a service. As a result, we posit:

H5: Perceived cost negatively affects borrowers, satisfaction of borrowing using DLAs.

H6: Perceived cost negatively affects continuance intention to borrow using DLAs.

2.2.4 Satisfaction (SAT)

Refers to a positive feeling that gives contentment; it arises from using a particular good or service. ECT suggests that SAT with a service is a primary motivation for borrowers to continue borrowing using DLAs. SAT arises from a positive CONF. (Bhattacherjee, 2001a, 2001b; Oghuma *et al*., 2016; Savitha *et al*., 2022). If an individual is dissatisfied, they will stop using this particular service for credit and maybe opt for other options. The Satisfied are the only ones who can

choose to continue using a particular service. COIN to borrow refers to the post-acceptance, usually already determined by individuals' SAT and or PU of borrowing using DLAs (Humbani & Wiese, 2019).

H7: Satisfaction has a positive impact on continuance borrowing intentions

2.2.5 Continuance Intention to Borrow (COIN)

Refers to the intention of users to continue using this app service to acquire credit over time. In the context of DLAs, COIN is important for platform sustainability, as retaining borrowers is more cost-effective than acquiring new ones (Bhattacherjee, 2001a). Studies have shown that both SAT and PU positively influence COIN, but SAT often plays a more dominant role (Oghuma et al., 2016). This, therefore, implies the importance of maintaining a high level of user SAT to ensure long-term engagement with digital lending platforms.

Since existing literature provides a strong foundation for understanding the relationships between CONF, PU, PC, SAT, and COIN, there remains a need for further exploration in the context of digital lending. Most studies have focused on e-commerce or general FinTech services, with limited attention paid to how these constructs interact specifically within DLAs. Additionally, much of the existing research has been conducted in developed markets, leaving a gap in the understanding of how these factors play out in emerging economies such as India, where financial inclusion and digital literacy are still evolving (Yu & Zhang, 2021).

3. Research Methodology

3.1 Overview of Sample and Procedures

This study adopts a quantitative research approach to examine relationships from the hypothesis derived from the ECM. The target population was anyone with experience in using DLA loans was found to be eligible to fill out the questionnaires. The criteria for the population was that everyone who was 18 years old and above, and had used the DLA at least once. The purposive sampling technique was used to make sure that only relevant participants were surveyed. Questionnaires were distributed both physically and digitally (via Google Forms), with translations available in English, Hindi and Malayalam to enhance accessibility.

To warrant the clarity and relevance of survey items, a pilot study was conducted among 20 respondents from different backgrounds. By this, we mean different age groups, occupations, and levels of education. The feedback we obtained from the pilot study was vital to refine the questionnaire for easy understanding and devoid of ambiguity. The final questionnaire used comprised two sections: demographic information and model constructs. The latter included items measured on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). All constructs, i.e., PU, CONF, SAT, PC and COIN, utilised scales adapted from validated instruments in prior studies (Bhattacherjee, 2001 & Flake *et al*., 2018). These scales were then rephrased to suit the DLA context.

3.2 Data Analysis

The responses were screened and cleaned after data collection for completeness, resulting in 349 valid entries for this particular study. The demographic variables were summarised using IBM SPSS 23.0, while the primary analysis was conducted using IBM AMOS most preferred due to its capability of testing the suitability of a theory in studying a particular area (Dash & Paul, 2021). We first performed Confirmatory Factor Analysis (CFA) to validate the measurement model by evaluating the convergent and discriminant validity. Following CFA, we employed SEM in AMOS to test the hypothesised relationships between the constructs (Kline, 2018). Model fit was evaluated using standard indices, including the Comparative Fit Index (CFI), Normed Fit Index (NFI) and Root Mean Square Error of Approximation (RMSEA). The results indicated a good model fit, enabling further interpretation of path coefficients and their significance.

4. Results and Discussions

4.1 Results Analysis

4.1.1 Descriptive Analysis

The demographic data were summarised using IBM SPSS. 23.0. Table 1 presents a detailed breakdown of the gender, age, income and educational levels of

respondents. The majority of respondents were male (57.6%), with females making up 42.4% of the sample. Most participants (69.9%) belonged to the 18-29 age group, followed by 19.5% aged 30-45. Over half of the respondents (51.6%) earned below ₹1.25 lakhs annually, and 28.7% fall in the ₹1.25-5 lakh bracket with the largest education group having a bachelor's degree (37.2%), followed by those with a master's degree (33.0%).

Table 2 shows descriptive and bivariate correlations, where bivariate correlations of CONF show the strongest relationship with PU (r = 0.618), indicating that those with higher expectation confirmation tend to perceive the system as more useful. The highest mean score is for PU (M = 3.2321), and the lowest is for COIN (M = 2.3947), suggesting that while users find the system useful, fewer are likely to continue using it. SAT is highly correlated with COIN (r = 0.505), indicating that higher SAT significantly increases the likelihood of continued use.

4.1.2 The Reliability and Validity Analysis

The reliability and validity of the constructs were all assessed using CFA as shown in Table 3. All the standardised factor loadings fall above 0.7 (Hair *et al*., 2017), with the least at 0.76, hence showing a good convergent validity for the indicators, as shown in Table 3. The reliability and validity analysis for the five constructs, CONF, PU, PC, SAT, and COIN, showed that all constructs met the required thresholds. The constructs demonstrated strong internal consistency with a Cronbach's Alpha (CA) ranging from 0.844 to 0.913 which is within the requirements. The Composite Reliability (CR) values for all constructs were well above 0.7 all ranging from 0.839-0.914 and the Average Variance Extracted (AVE) for all constructs exceeded the 0.5 mark establishing a fitting convergent validity with the AVE ranging from 0.512-0.727 (Hair *et al*., 2017; Larcker, 1981; Sarstedt *et al*., 2016).

We performed the CFA using IBM AMOS 24.0 to validate the factor structure variables under the focus of this study. Figure 1 presents the CFA, which displays the five latent variables measured by AMOS, i.e., CONF, PU, PC, SAT, and COIN. Through the analysis of CONF, PU, PC, SAT, and COIN using IBM AMOS, we generated vigorous reliability and validity indicators suitable for the study of continuance usage of DLAs. The CR and CA values for all constructs were well above the recommended 0.7 threshold, with the lowest being 0.844 for CA and 0,838 for CR, all for PC, the highest being COIN, with 0.913 and 0.914 for CA and CR respectively. This indicated a high level of internal consistency within the constructs. The values indicating AVE were all above the 0.5 mark, with PC having the least at 0.512 and COIN the highest at 0.727, which indicated satisfactory convergent validity (Hair *et al*., 2017). From these results, we concluded that the constructs were both reliable and valid enough to measure their respective latent variables and, hence, qualified for additional hypothesis testing and analysis

Table 1. Demographics

Characteristics	Category	Quantity	Per cent %
Gender	Male	201	57.6
	Female	148	42.4
Age	18-29	244	69.9
	30-45	68	19.5
	46-60	33	9.5
	Above 60	4	1.1
Income	Below 1.25 lakhs	180	51.6
	1.25-5 lakhs	100	28.7
	5- 30 lakhs	56	16.0
	Above 30 lakhs	13	3.7
Education	Less than 12th STD	16	4.6
	Completed 12th STD	58	16.6
	Diploma/Certificate	23	6.6
	Bachelors	130	37.2
	Masters	115	33.0
	PhD and Above	5	1.4
	Others	2	0.6

Source: Authors work

Table 2. Descriptive and bivariate correlations

Constructs	Mean	SD	PU	CONF	PC	SAT	COIN
PU	3.2321	0.85530	1	.618**	.155**	.450**	.328**
CONF	3.0451	0.76184	.618**	1	.121*	.453**	.372**
PC	3.2688	0.62355	.155**	.121*	1	.119*	0.090
SAT	2.7378	0.82982	.450**	.453**	.119*	1	.505**
COIN	2.3947	0.85255	.328**	.372**	0.090	.505**	1

Source: Authors work

Table 3. Reliability and Validity

Construct	Code	Standardised Loading	Cronbach's Alpha	AVE	Composite Reliability
CONF	CON1	0.802	0.876	0.643	0.878
	CON2	0.847			
	CON3	0.871			
	CON4	0.767			
PU	PU1	0.768	0.875	0.642	0.877
	PU2	0.852			
	PU3	0.858			
	PU4	0.763			
SAT	SAT1	0.849	0.902	0.700	0.903
	SAT2	0.853			
	SAT3	0.885			
	SAT4	0.799			
COIN	COIN1	0.840	0.913	0.727	0.914
	COIN2	0.878			
	COIN3	0.865			
	COIN4	0.853			
PC	PC1	0.775	0.844	0.512	0.839
	PC2	0.745			
	PC3	0.748			
	PC4	0.713			
	PC5	0.717			

Source: Authors work

in the structural equation model. According to Table 5, all the HTMT values were below the recommended threshold of 0.85, this confirmed that the constructs had adequate discriminant validity. Meaning constructs in the model measure distinct concepts, which is essential for the integrity of the structural model and the reliability of the analysis (Henseler *et al*., 2015).

The structural model was evaluated using SEM through IBM AMOS Figure 2. The model fit indices indicated that it had a good fit and, hence, was appropriate for this study. The standard factor loadings are all above 0.7, which is strong enough to show good convergence validity for the indicators. This shows that the data set fits the hypothesized measurement model. All measurements of items had loadings greater than 0.70. Table 6 shows that the model demonstrated an excellent fit based on various fit indices. The default model has a CMIN of 340.553 with 181.000 Degrees of Freedom (DF), resulting in a CMIN/DF ratio of 1.882, which falls within the acceptable range (between 1 and 3), indicating a good model fit. The baseline comparisons show a CFI of 0.964, NFI of 0.926, and IFI of 0.964, all indicating excellent fit as they exceed the 0.95 threshold. The RMSEA is 0.050, with a PCLOSE value of 0.463, reflecting a close

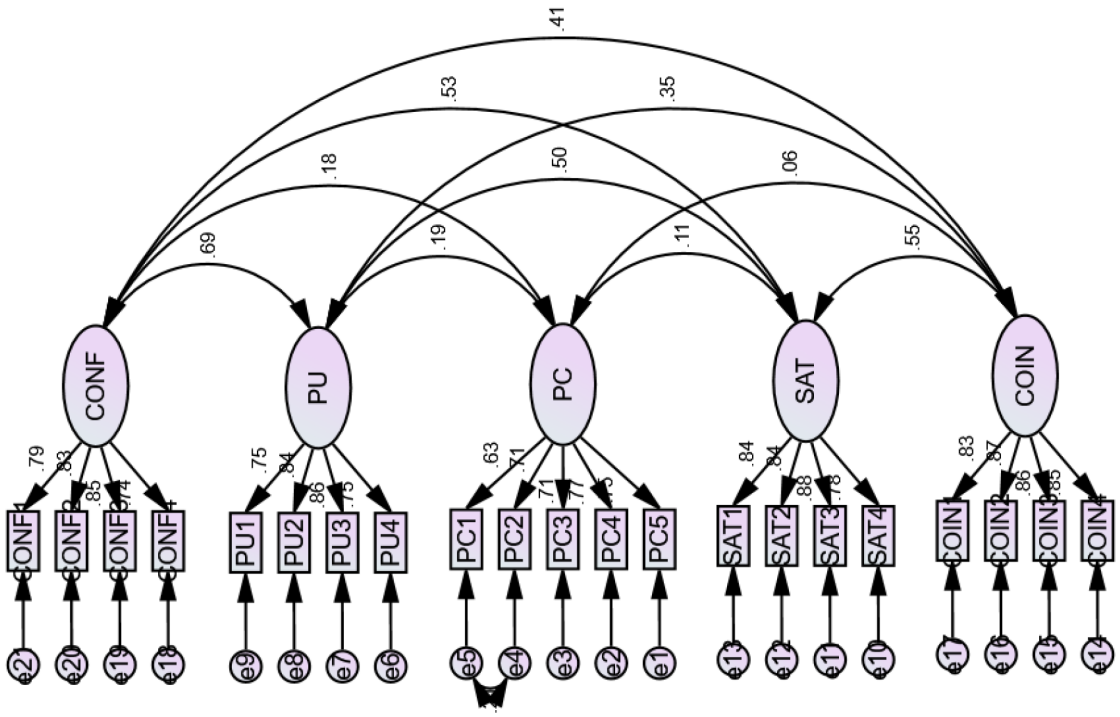


Figure 1. Confirmatory factor analysis (CFA).

Source: Authors work

fit. Parsimony-adjusted measures, such as PNFI (0.798) and PCFI (0.831), indicated a parsimonious model. These results overall indicated that the hypothesized model is appropriate for testing and proposed relationships.

4.1.3 Hypotheses Testing

The proposed hypotheses were tested using the path analysis procedure. The path coefficients and their significance levels are presented in Table 7. The results

Table 4. Descriptive reliability and validity measures of constructs

Constructs	CR	AVE	MSV	MaxR(H)	PC	PU	SAT	COIN	CONF
PC	0.839	0.512	0.035	0.845	**0.716**				
PU	0.877	0.642	0.47	0.886	0.187**	**0.801**			
SAT	0.903	0.7	0.305	0.907	0.107†	0.505***	**0.837**		
COIN	0.914	0.727	0.305	0.915	0.055	0.348***	0.552***	**0.853**	
CONF	0.878	0.643	0.47	0.884	0.176	0.685	0.525	0.406	**0.802**

Source: Authors work

Table 5. Discriminant validity (HTMT ratio)

Constructs	PC	PU	SAT	COIN	CONF
PC					
PU	0.206				
SAT	0.099	0.505			
COIN	0.046	0.366	0.564		
CONF	0.185	0.703	0.525	0.415	

Source: Authors work

Table 6. Model fit

Measure	Estimate	Threshold	Interpretation
CMIN	340.553	--	--
DF	181	--	--
CMIN/DF	1.882	1-3	Excellent
CFI	0.964	>0.95	Excellent
SRMR	0.072	<0.08	Excellent
RMSEA	0.05	<0.06	Excellent
PClose	0.463	>0.05	Excellent

Source: Authors work

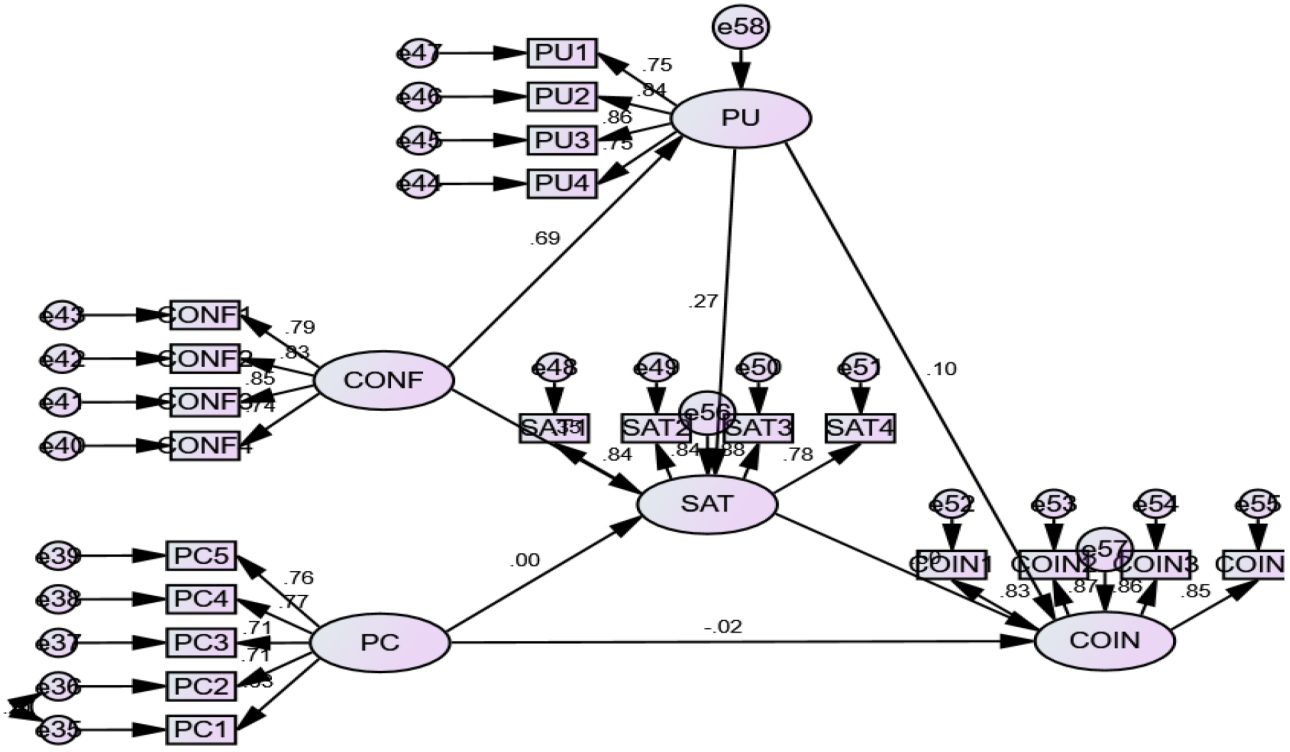


Figure 2. The structural equation modelling (SEM).

Source: Authors work

Table 7. Hypotheses tests (direct relationships)

Hypotheses	Estimate	S.E.	C.R.	P	Decision
PU<---CONF	0.784	0.077	10.185	***	Accept
SAT<---PC	0.006	0.069	0.08	0.936	Reject
SAT<---CONF	0.418	0.096	4.342	***	Accept
SAT<---PU	0.279	0.083	3.365	***	Accept
COIN<---PC	-0.022	0.069	-0.322	0.747	Reject
COIN<---PU	0.109	0.064	1.702	0.089	Accept
COIN<---SAT	0.501	0.065	7.742	***	Accept

Path coefficients and significance; table with hypotheses test results
N/B: ***p<0.01; **p<0.05 & *p<0.10
Source: Authors work

show that CONF significantly influences PU and SAT, with estimates of 0.784 ($p < 0.001$) and 0.418 ($p < 0.01$), respectively. Perceived usefulness also has a positive impact on satisfaction (estimate = 0.279, $p < 0.01$) and COIN (estimate = 0.109, $p < 0.10$). However, perceived cost (PC) was found to have an insignificant effect on both SAT and COIN, with p-values of 0.936 and 0.747, respectively. This implied that borrowers preferred platform functionality and satisfaction over cost considerations.

These findings indicate that user satisfaction is the most critical factor driving continued usage intention, while perceived cost plays a minimal role. The importance of managing user expectations and ensuring a positive experience is emphasised to enhance long-term engagement.

4.2 Discussion

This study sheds light on the post-adoption behaviour of DLA users, focusing on key factors influencing their continued usage intentions. The results support the application of the ECM in the context of digital lending. The strong relationship between confirmation and perceived usefulness shows the importance of meeting user expectations to boost perceived benefits. These findings reveal that confirmation of expectations positively influences both perceived usefulness and satisfaction, indicating that users' confirmation of expectations plays a key role in shaping both the borrowers' perception of usefulness and their overall satisfaction with the credit service. This points out the strong relationship between confirmation of expectations and perceived usefulness, highlighting the key responsibility that management of expectations does in influencing borrowers' ongoing perceptions of platform value, which is consistent with previous studies (Bhattacherjee, 2001b; Lee & Kwon, 2011). In the digital lending platforms context, this means that transparent communication and consistent service delivery are important for enhancing perceived usefulness. Similarly, perceived usefulness has a moderate positive impact on satisfaction, indicating that borrowers' perceptions of the platform's usefulness add up to their overall satisfaction, although to a lesser extent compared to the direct effect of confirmation of expectations. Satisfaction emerged as the dominant factor influencing continuance intention, emphasising the need for platforms to prioritise user experience. The influence of perceived usefulness on continuance intention to borrow is relatively low but still significant, suggesting that when usefulness affects users' intent to continue using the platform, it is not the primary driver (C.C & Prathap, 2020; Hong *et al*., 2006; Oghuma *et al*., 2016). The post-adoption perceived usefulness represents a weaker predictor of continuance intention to borrow than satisfaction (Susanto *et al*., 2016).

Unexpectedly, the perceived cost had an insignificant influence on both satisfaction and continuance intention to borrow, implying that borrowers may endure higher costs if the service provides sufficient value. This suggests that borrowers are neither dissuaded nor influenced by costs associated with borrowing using these DLA platforms. This finding aligns with prior studies indicating that convenience and functionality often outweigh cost considerations in digital service adoption (Sarosa, 2021). As is the case of users of digital services, borrowers tend to tolerate high costs if they are satisfied with the services, benefits, and functionalities they receive. For instance, the process of acquisition and disbursement of the loan is quick and without a lot of technicalities which causes the borrowers to be satisfied with the service regardless. On the contrary, these results emphasise the importance of satisfaction in determining continuance intention to borrow, with satisfaction showing the strongest effect on users' intention to continue using the platform. This finding shows that satisfaction is a key factor in the development of user loyalty and engagement, aligning with the broader literature that satisfaction is a key

determinant of continued usage behaviour. As both confirmation of expectations and perceived usefulness contribute to user satisfaction, it is satisfaction itself that bears the most significant influence the most significant role in influencing users' continuance intention to borrow (Wang & Lin, 2021). These findings emphasise the importance of providing a positive user experience and ensuring that the expectations of the borrowers are diligently met to enhance both perceived usefulness and satisfaction, ultimately increasing continued usage.

From a non-technical perspective, this study highlights that users prioritise convenience, seamless processes, and overall satisfaction over financial costs. Policymakers and platform developers can use these insights to design better regulatory frameworks and service models that balance user needs with business objectives. Future efforts may explore the nuanced role of other factors, such as trust and perceived risk, in shaping post-adoption behaviour.

5. Conclusion, Implications and Limitations

This study explores user behaviour in digital lending applications using the ECM. It reveals that confirmation of expectations significantly influences User Experience and SAT, influencing borrowers' intention to continue using the platform. Our study emphasises the importance of meeting or exceeding user expectations, particularly in terms of perceived benefits and utility. Perceived usefulness showed a weaker direct effect on continuance intention to borrow than satisfaction, suggesting that the DLA borrowers appreciate the functional benefits derived from them but are more driven by the overall satisfaction of the platform. We found that satisfaction is the most significant predictor of continuance intention to borrow, highlighting the need for platforms to meet functional expectations and provide a satisfying experience for their clients. The study also records a diminishing role of cost in the borrower's decision-making; hence, much emphasis should be concentrated on the design and management of digital lending platforms, emphasising the importance of delivering reliable, efficient, and user-friendly services that consistently meet or exceed customer expectations.

These findings contribute to the growing body of literature on the post-adoption behaviour of DLAs context. Our research extends our understanding of how confirmation of expectations, perceived usefulness, and satisfaction influence continuance intention to borrow through the utilisation of the ECM. This research extends the ECM by incorporating perceived cost and testing it in a digital lending context. This is particularly relevant to understanding how users form long-term relationships with financial technologies, offering valuable insights for refining the ECM in the context of FinTech and DLAs.

The study highlights the importance of user satisfaction as a key driver of customer retention in DLAs. To enhance user experiences, managers should simplify loan processes, offer efficient customer support, and ensure a seamless borrowing journey. A system should be implemented to ensure borrowers' expectations are managed properly to maintain trust and meet user expectations. Financial Service Providers (FSPs) should focus on delivering what they promise, realigning platforms' capabilities with marketing and product information, and incorporating features like personalised loan offers, flexible repayment options, and user-friendly interfaces. Operational excellence is also crucial for promoting trust and satisfaction. Maintaining regulatory compliance and transparency in loan terms, interest rates, and data privacy will further build user trust.

This research, like any other, is devoid of shortcomings. However, this study offers several opportunities for further exploration. Firstly, the data used was collected via questionnaires from borrowers of digital loans; the data was self-reported and cross-sectional in nature, which would introduce response bias as participants may misrepresent their borrowing behaviours or satisfaction levels and could also limit the ability to infer causality between constructs. It is therefore suggested that future studies could consider incorporating objective measures, such as data from digital lending platforms, to improve the accuracy of findings. Longitudinal studies, which could help track changes over time and provide stronger evidence for the causal relationships between confirmation of expectations, perceived usefulness, satisfaction, and

continuance intention to borrow should be considered. As the study uses ECM constructs and perceived cost, it would be important to incorporate other factors like trust, perceived risk, and financial literacy for a comprehensive understanding of user behaviour on digital lending platforms. Future research may also investigate pre-adoption aspects like initial trust and perceived barriers to adoption.

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