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UTAUT-3-Based Analysis of User Intention and Usage Behavior in Digital Lending Adoption

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ABSTRACT: Technological developments in the banking sector continue to advance rapidly, particularly with the rise of mobile banking applications that enable users to perform transactions anytime and anywhere. These innovations have significantly transformed the banking service industry. The purpose of this study is to analyses the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habits, and personal innovativeness on behavioral intention and use behavior in using mobile banking applications in the Chennai region. Additionally, the study aims to identify the most dominant variable influencing behavioral intention and use behavior. This research employed a quantitative method using primary data collected from 210 respondents. The sampling technique used was non-probability sampling with a purposive sampling approach. Data were analyzed using Structural Equation Modelling (SEM) with the help of AMOS software. The findings reveal that performance expectancy, habits, and personal innovativeness have a positive and significant impact on behavioral intention. Furthermore, facilitating conditions, habits, and behavioral intention significantly influence use behavior. Among all variables, performance expectancy emerged as the most dominant factor affecting behavioral intention.

Keywords: UTAUT3, mobile banking, behavioral intention, use behavior, performance expectancy, personal innovativeness, Chennai, SEM, AMOS.

I. INTRODUCTION

Fintech has expanded significantly during the past four years. Fintech is defined as innovation and disruption in the provision of financial services by non-financial firms through the use of IT [1]. Fintech in Indonesia encompasses digital payments, crowdfunding, peer-to-peer (P2P) lending, account aggregators, information and feeding sites, and personal finance, according to the Indonesian Financial Services Authority (OJK) [2]. Many fintech lending firms have emerged as a result of the growing market demand for borrowing money through online platforms. This fintech loan is registered with the Financial Services Authority (OJK) and the Ministry of Information and Technology (Communication and Information), two Indonesian regulatory bodies. Numerous fintech lending businesses that are not registered but nevertheless function in Indonesia exist in addition to those that are registered at these institutions (regulated). Fintech lending of this kind is referred to as "illegal lending" (unregulated). In comparison to 2018, the number of illicit loan sources discovered in 2019 has doubled. This illicit lending is still expanding in spite of the Indonesia Financial Services Authority's (OJK) efforts to stop it.

According to [3], a number of theoretical research models that address user acceptability and adoption of new information technology advances with various emphasis have been developed and tested in many situations and nations. In the financial industry, financial technology, or FinTech, has changed the game in recent years. The entire manner that business is conducted has been transformed by fintech. In order to deliver financial solutions that are far more efficient than those offered by traditional financial institutions, financial technology essentially combines technology and finance. However, the conventional banking system cannot be replaced by FinTech. However, FinTech serves as a platform for efficient banking services. Nowadays, new technologies like machine learning, big data analysis, and algorithms are used to deliver the majority of banking services. An integrated approach to banking is taken by traditional banking systems.

The fundamental functions of a traditional banking system are deposit collecting and lending, together with auxiliary operations like remittances, point of sale, insurance, and so forth. FinTech-enabled businesses, primarily startups, tend to concentrate on certain banking functions rather than implementing an integrated strategy. While some FinTech companies concentrate on payment services, remittances, and insurance, few FinTech companies concentrate on digital lending. Another name for digital lending is alternative lending. Alternative lending is the term for online platforms that offer affordable loans that are easy for the sizable untapped market segment to get. A burgeoning sector of digital lending, alternative lending targets a range of borrowing requirements, such as working capital loans, payday loans, small- and medium-sized business loans, and consumer loans. Both individual and institutional investors find it to be a comparatively less volatile asset type. Digital lending platforms and the enablers that support them, like white label services and alternative credit scores, make up the majority of the sector. These platforms link lenders looking for better profits than banks currently provide with borrowers looking for quick, short-term loans. According to [4], digital lending offers greater potential in India, where over $1 trillion in retail loans could be disbursed digitally over the course of the next five years, until 2023.

Digital payments, cryptocurrency, smart contacts, Insurtech, Reg Tech, Robo-advisors, cyber security, online banking, e-commerce, etc. are just a few of the many FinTech services that are being advertised and made available to consumers by a variety of industries, including capital markets, banks, insurance companies, blockchain companies, and retailers [5-9]. Additionally, [10]. noted that FinTech is bringing about a significant transformation by making modern financial transactions for retailers and their customers safe, prompt, easy, and efficient. Given the success and popularity of FinTech services, a number of non-financial corporations have begun offering their customers m-payment services, including Google (Google Pay), Apple (Apple Pay), Samsung (Samsung Pay), and others. Non-financial organizations are implementing FinTech services at a rapid rate of growth because they enable consumers to download their mobile applications, register, and conduct m-payment transactions globally. India's internet users at the start of the internet boom were millennials, men, and city dwellers [4]. However, this situation is now over, and internet usage is widespread in India. According to Boston Consulting Group [4] research on customer behavior throughout the purchasing process, half of loan applicants with internet access make their loan purchases online.

Additionally, the report indicates that the expansion of digital infrastructure in India and the preparedness of Indian consumers will propel the rise of digital lending at an exponential rate. Over the next five years, the entire value of digital lending in India is predicted to surpass $1 trillion [4]. The two most popular digital loans among consumers are small-to medium-sized business loans and personal loans, which are followed by home loans. financial services firms can now expand financial inclusion in India thanks to technology. These days, possessing an Aadhaar number and a cell phone are differentiators. One billion Indians currently possess either an Aadhaar card or a cell phone. Now that they have one or both of these facilitators, the unbanked in India have a chance to take advantage of the official financial system. Not standing the impressive impact that digital lending has on the Indian lending market, there are several barriers to its expansion. Increasing the maximum amount of digital loans through One-Time Password-based e KYC from Rs 60000 to Rs 5,00,000 and amending section 138 of the Negotiable Instruments Act, 1881 to allow for digital signatures (e-signs) on loan documents are two measures that could expand the reach and expansion of digital lending.

Permit e-mandate for digital loan disbursement collecting. A study that looked at eight popular models/theories of technology adoption/appropriation from earlier studies led to the development of UTAUT. These eight pre-existing models were reviewed in the literature before the UTAUT model was first developed. Venkatesh et al. (2003) [11], used the categories of anxiety, self-efficacy, social influence, enabling conditions, performance expectancy, effort expectancy, and attitude toward using technology in their study. Three determining elements were removed after passing previous tests, leaving four primary component performance expectancy, effort expectancy, social impact, and facilitating conditions that directly influence usage intention and behavior.

- Working Mechanism of Lending applications: In the global and Indian financial services industries, digital lending is a fast-expanding business. These factors include internet usage, big data and technology developments, digital ecosystems, creative models, time savings, and customer-friendly strategies.
- Internet utilization: The current era is digital. People's behavior patterns are constantly evolving on a global scale. These days, e-commerce websites, digital government pushes, cashless economy, and other factors are driving the Indian population's heavy reliance on online transactions. The percentage of Indian urban dwellers who made purchases online rose from 7% in 2014 to 30% in2018 [4].
- Information technology and large data: Cloud computing, big data, analytics, blockchain technology, artificial intelligence, and other technological developments have completely changed how businesses operate today. The emergence of new financial technology firms was facilitated by these technologies. Digital lending companies are among these financial technology firms.
- Digital environment: For the growth of digital lending, a friendly digital ecosystem is crucial, in addition to consumer behavior. India is a leader in developing an environment that supports the growth of Fin Techs and online commerce. Because of the digital environment and efforts like Aadhar, the Unified Payment Interface (UPI), the Bharat Bill Payment System, the push for a cashless economy, and the Goods and Services Tax (GST), digital lending expanded dramatically.
- Creative Models**:** FinTech firms' innovative business models, such as point-of-sale based lending, invoice discounting exchanges, bank-FinTech partnerships, capital float, market place lending, and bank-led digital models, transformed the financial services sector in general and the lending sector in particular.
- A customer-focused and time-saving strategy: Getting a loan online isn't always difficult or time-consuming. However, the procedure of digital lending is actually quite easy and intelligent. Regarding method, cost, and time, it has benefits. This technique is used to process and disburse digital loan.

1. RESEARCH QUESTION

- What factors influence users' intention to adopt digital lending platforms based on the UTAUT-3 model?
- How does behavioral intention affect the actual use of digital lending services?
- What role does personal innovativeness play in shaping users' intention to adopt digital lending?

2. OBJECTIVES

- To examine the impact of key UTAUT-3 constructs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit) on users' intention to adopt digital lending platforms.
- To analyses the effect of behavioral intention on the actual use behavior of digital lending services.
- To investigate the role of personal innovativeness in influencing users' intention to adopt digital lending.

To assess the applicability and explanatory power of the UTAUT-3 model in the context of digital lending adoption.

II. THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

1. THE EFFECT OF PERFORMANCE EXPECTANCY ON BEHAVIOURAL INTENTION

The degree to which a person is positive that using a specific technology would enable them to optimize their task performance is known as performance expectancy [11, 12]. Performance expectation is a key determinant of consumers' intention to adopt information technology, according to [13] came to the conclusion that customers' intention to use FinTech services is highly influenced by performance expectations. Previous research has thus demonstrated that performance expectancy is a key component of

UTAUT, which aids in the researcher's comprehension of users' intentions to utilize FinTech services [14, 15]. Similar to this, [19] empirical study from Australia in 2022 verified a substantial and positive correlation between consumers' behavioral intention toward Fin-Tech and online loan services and performance expectancy. Performance expectancy is the degree to which consumers can profit from the technology they utilize to carry out their tasks [16]. One of the most important factors in determining a user's willingness to accept technology financial services like internet banking, mobile banking, and mobile payments is performance expectancy. Consumers are more likely to embrace and use new technology if they believe it will improve their daily life [17]. It is possible to forecast intention when using mobile lending technology, [18] concluded in their research on performance expectancy with the conclusion that it is possible to predict intention in the use of mobile lending technology. In this study, performance expectancy refers to the user's belief that the mobile lending apps are useful in facilitating efficient and effective for getting loans.

- H1 Performance expectancy has a positive and significant effect on behavioral intention

2. THE EFFECT OF EFFORT EXPECTANCY ON BEHAVIOURAL INTENTION

The concept of effort expectancy, which is the same as perceived ease of use, is the degree to which consumers can achieve a technology's ease of use [11]. Study [19] claims that effort expectancy describes how users perceive a system or technology depending on how simple it is to use. A direct correlation between effort expectancy and consumers' behavioral intention to utilize FinTech was previously studied by a number of academics. The relationship between effort expectancy and behavioral intention to use FinTech services was examined by [20], who established a framework and found a strong and positive link. Study [21] verified the same findings. Study [22] has conducted a study in which they discovered that behavioral intention to utilize FinTech services is significantly impacted by effort expectancy. Users of digital lending services will prefer to use it if they feel at ease doing so, according to [23]. Effort Expectancy has played a major role in the systems and fintech services. Studies [24, 25] propose that the more convenience and comfort that m-lending services offer, the more likely it is that consumers will be drawn to use them for their banking needs. Mobile lending services are more digitally friendly and accessible due to the systems' ease of use (EE). According to [26], it provides users with a positive user experience by facilitating easy and secure user access and authorization. Enhanced card control, budgeting tools, account opening, text banking, wearable widgets, and rapid payments are just a few of the extra EE features financial institutions especially banks, can offer in m-banking to entice new customers. Researchers contend that people's intention to utilize m-lending services (MLS) is strongly correlated with the degree of effort expectancy (complexity and ease of use) (e.g., [27, 28].

- H2 Effort expectancy has a positive and significant effect on behavioral intention

3. THE EFFECT OF SOCIAL INFLUENCE ON BEHAVIOURAL INTENTION

According to [11], social influence is the extent to which a user values other people more friends, family, leaders, etc. and supports the usage of the new system and/or technology. According to [29], social impact may be a significant component of UTAUT, which aids in forecasting user behavior that may indicate internalization, identification, and compliance. But identification and internalization cause a user's beliefs to change based on their social standing [30], while compliance modifies beliefs based on subjective norms [31]. However, the high correlation between social impact and consumers' behavioral intention to utilize FinTech services in various circumstances was examined in empirical investigations. For instance, a survey conducted in China by [32] revealed that social influence had a considerable impact on users' behavioral intention to utilize FinTech services. Also, [33] conducted another empirical study in India and concluded that there is a strong correlation between users' behavioral intention to use FinTech services and social influence, as social influence is a significant indicator of UTAUT that supports users' actual beliefs and intentions towards FinTech services. Accordingly, [34] highlighted that people may be more inclined to use digital financial services that aid in better money management in a society that places a high emphasis on saving and investing. However, consumers may be less inclined to use digital financial services in a society where traditional banking methods are more ingrained because they may prefer to continue using what they know [35]. An individual may be more inclined to use FinTech services, for example, if they come from a household that values technology use and financial literacy. For example, social factors including family customs and culture might have a big impact on Saudi Arabia's acceptance of FinTech services [34]. Social influence affects people's adoption of technology through three mechanisms: identification, internalization, and compliance. The consequences of this influence are multifaceted and impacted by a number of unanticipated factors [36, 37].

- H3 Social influence has a positive and significant effect on behavioral intention

4. THE EFFECT OF FACILITATING CONDITIONS ON BEHAVIOURAL INTENTION

[11] define enabling conditions as the extent to which users have a strong belief that the technological infrastructure of an organization can completely support their usage of a system and/or technology for improved performance. According to [38], technical innovation also helps users comprehend problems that arise during technical tasks and figure out how to solve them effectively. These activities are also sufficient for the users' positive and satisfying experiences [39]. The beneficial effect of favorable conditions on the use of FinTech services in Indonesia was recently confirmed by [40]. Study [26] also looked at the relationship between FinTech services and conducive conditions, but they found it to be weak. In this context, they talked about how the idea of FinTech services is still cutting edge in a number of developing nations, where businesses encounter several obstacles in helping people utilize FinTech services for more efficient, timely, and better financial transactions. In the context of a knowledge management system,[41] confirmed the impact of enabling conditions on technology use. Study [23] also provided support for the favorable and important link of facilitating conditions in the context of e-banking services.

- H4 Facilitating conditions has a positive and significant effect on behavioral intention

5. THE EFFECT OF HEDONIC MOTIVATION ON BEHAVIOURAL INTENTION

Hedonic motivation is the term used to characterize the usage of technology by customers who are motivated to experience pleasure and joy; it has been demonstrated to be a significant factor in deciding the acceptance and use of technology [42]. It has been demonstrated that perceived enjoyment, a concept related to hedonic motivation, directly influences people's adoption and usage of technology [43]. Likewise, hedonic desire was shown to be a predictor of behavioral intention to employ a technology by [11, 44]. According to research conducted by [16, 45, 46], it has been established that hedonic motivation significantly and favorably affects behavioral intention.

- H5 Hedonic motivation has positive and significant effect on behavioral intention

6. THE EFFECT OF PRICE VALUE ON BEHAVIOURAL INTENTION

As defined by [16] habit is the tendency for people to carry out actions automatically as a result of experience. It was discovered that in an online learning environment, habit directly influences behavioral intention [47] Similarly, similar outcomes in web technology for travel advising were reported by [48]. Additionally reinforces the beneficial association between habit as an automatic behaviors and behavioral aim. Building on research by [16, 49, 50] price value defined in this study as the trade-off between the advantages of using the mobile banking application and the expenses associated with the transactions has been demonstrated to impact behavioral intention.

- H6 Price value has positive and significant effect on behavioral intention

7. THE EFFECT OF HABIT ON BEHAVIOURAL INTENTION

As defined by [16] habit is the tendency for people to carry out actions automatically as a result of experience. It was discovered that in an online learning environment, habit directly influences behavioral intention [47]. Similarly, similar outcomes in web technology for travel advising were reported by [48]. Additionally, [51] reinforces the beneficial association between habit as an automatic behaviors and behavioral aim. It is confirmed by research by [16, 49, 52] that conducive conditions have a positive and significant influence on use behaviors. The degree to which users believe that technical support and the supporting infrastructure can help them use the mobile banking application is indicated by the term "facilitating conditions" in this study.

- H7 Habit has positive and significant effect on behavioral intention

8. THE EFFECT OF PERSONAL INNOVATIVENESS ON BEHAVIOURAL INTENTION

It is confirmed that personal innovativeness has a positive and significant influence on usage patterns, in line with research conducted by [49] and [46]. According to this study, a person's willingness to embrace technology advancements, such as mobile banking applications, is referred to as their personal innovativeness. In this study, the UTAUT model gained a new attribute: personal innovativeness (PI). PI indicates how far ahead of the curve a person is in embracing a new system or technology [80]. New technology or methods are more likely to be experimented with by those with greater inventiveness [81]. Numerous empirical research has demonstrated the tight relationship between employee innovativeness and behavioral intent to use technology [82, 83]. Study [27] showed in their descriptive results that the majority of Fintech users are under 35 years old.

- H8 Personal innovativeness has positive and significant effect on behavioral intention

III. UTAUT-3 ANALYSIS OF DIGITAL LENDING ADOPTION

1. THE EFFECT ON FACILITATING CONDITIONS ON USE BEHAVIOUR

Facilitating environments have a good and significant influence on consumption behaviors, according to research conducted by [16, 49, 52]. The degree to which users think that infrastructure and technical support can make utilizing the lending app easier is referred to in this study as "facilitating conditions." Therefore, it is hypothesized that:

- H9: Facilitating Conditions has a positive and significant effect on Use Behavioral

2. THE EFFECT HABIT ON USE BEHAVIOUR

It is confirmed by research by [16, 49, 52], that conducive conditions have a positive and significant influence on use behaviors. The degree to which users believe that technical support and the supporting infrastructure can help them use the mobile banking application is indicated by the term "facilitating conditions" in this study. As a result, the hypothesis posited is as follows:

- H10: Habits has a positive and significant effect on Use Behavioral

3. THE EFFECT PERSONAL INNOVATIVENESS ON USE BEHAVIOUR

It is confirmed that personal innovativeness has a positive and significant influence on usage patterns, in line with research conducted by [49] and [46]. According to this study, a person's propensity to embrace technology advancements, such as lending applications, is referred to as personal innovativeness. Consequently, the following hypothesis is put forth:

- H11: Personal Innovativeness has a positive and significant effect on Use Behavioral

4. THE EFFECT BEHAVIOURAL INTENTION ON USE BEHAVIOUR

Study [53] state that behavioral intention refers to the readiness to adopt and use a specific technology, as demonstrated in this case by the propensity to use the lending app. The following hypothesis is put out in light of this premise:

- H12: Behavioral Intention has a positive and significant effect on Use Behavioral

IV. STATEMENT OF THE PROBLEM

Lending takes place offline in conventional banking and other official financial systems. In the old system, the entire lending process from finding a potential borrower to approving the loan or credit is done by hand, which takes a lot of time and wears out the borrowers. To assess a borrower's credit worthiness, banks utilize conventional credit scores like the CBILS credit score. Conventional credit ratings are subject to specific restrictions and do not take into account the information that borrowers provide. Additionally, bankers only offer loans to clients with "Good Credit Scores" and those who can access the banks through bank accounts. As a result, despite the government of India's numerous financial inclusion attempts, individuals and businesses are unable to access banks, and those without strong credit ratings are shut out of the financial system. As a result, the conventional ban king system has a laborious and time-consuming lending process that financially excludes both individuals and enterprises. Digital financing has now addressed these loopholes. Digital financing is extremely quick, and loans are granted utilizing technology and alternative credit ratings at reasonable interest rates in a comparatively shorter amount of time. Some online lenders approve credit within a minute of receiving the necessary paperwork, and they offer a range of credit options to satisfy the various demands of both individuals and companies. Digital lending has transformed the lending process and become a viable substitute for bank loans. As a result, research on the development of digital lending as a substitute for bank credit is crucial, both in India and internationally. Therefore, the research gap of this study is addressed as the following:

- Lack of studies applying the full UTAUT-3 model specifically to digital lending services.
- Limited research on digital lending adoption focused on users in the Chennai region.
- Underexplored role of personal innovativeness in digital lending adoption behaviors.
- Insufficient analysis of habitual behaviors formation in the context of digital lending.
- Minimal use of UTAUT-3 moderators (for example, age, gender, experience) in digital lending studies.

V. THEORETICAL FRAMEWORK

Original UTAUT model was expanded upon by the Unified Theory of Acceptance and Use of Technology 3 (UTAUT-3), which serves as the theoretical basis for this investigation [16]. UTAUT-3 was created to better capture the adoption of technology in consumer contexts by adding new constructs like price value, habit, hedonic incentive, and personal innovativeness. Studies of digital lending, a self-driven, technology-mediated financial service that consumers engage with independently, frequently through cell phones or web platforms, benefit greatly from these enhancements since they provide a more comprehensive knowledge of how individuals embrace personal technologies. Four primary dimensions were included in the original UTAUT model, which was centered on organizational settings and included social influence, performance expectancy, effort expectancy, and facilitating conditions. By acknowledging the significance of internal drive (hedonic motivation), economic assessment (price value), behavioral patterns (habit), and individual characteristics (personal innovativeness), UTAUT-3, while maintaining these fundamental components, improves explanatory potency. Because of the multifaceted study of user behaviors made possible by these components, the model is especially well-suited to comprehending the uptake of digital lending, where decision-making is influenced by both utilitarian and subjective considerations. Performance expectancy, as it relates to digital lending, describes customers' perceptions of the value and advantages of utilizing digital lending platforms, including convenient access to credit, quicker loan approvals, and ease of use. The degree to which consumers believe the loan application process is simple or complicated is reflected in effort expectancy. A user's decision to utilize such services may be influenced by social influence, peers, or family, whereas facilitating conditions are the infrastructure, support, and resources that make use possible.

In this situation, UTAUT-3's extended variables are especially pertinent. The pleasure or contentment a user gets from utilizing a digital lending app is captured by hedonic motivation, which may not be as applicable in financial contexts but is still worthwhile to examine. Interest rates, convenience fees, and other hidden costs related to digital lending are examples of the cost-benefit trade-off that price value assesses. In the fintech industry, where early adopters frequently set market trends, habit gauges how much digital lending has become a user's automatic or routine behaviors, whereas personal innovativeness captures a user's innate propensity to experiment with new technologies. Lastly, this theoretical framework helps close the gap between user behaviors research and fintech innovation by informing the study's hypothesis generation and analytic structure. The application of UTAUT-3 to the digital lending setting in Chennai broadens the model's applicability to a comparatively unexplored area of financial technology. Additionally, it has significance for digital lending systems that aim to improve user engagement by identifying the behavioral and psychological elements that have the greatest impact on user adoption.

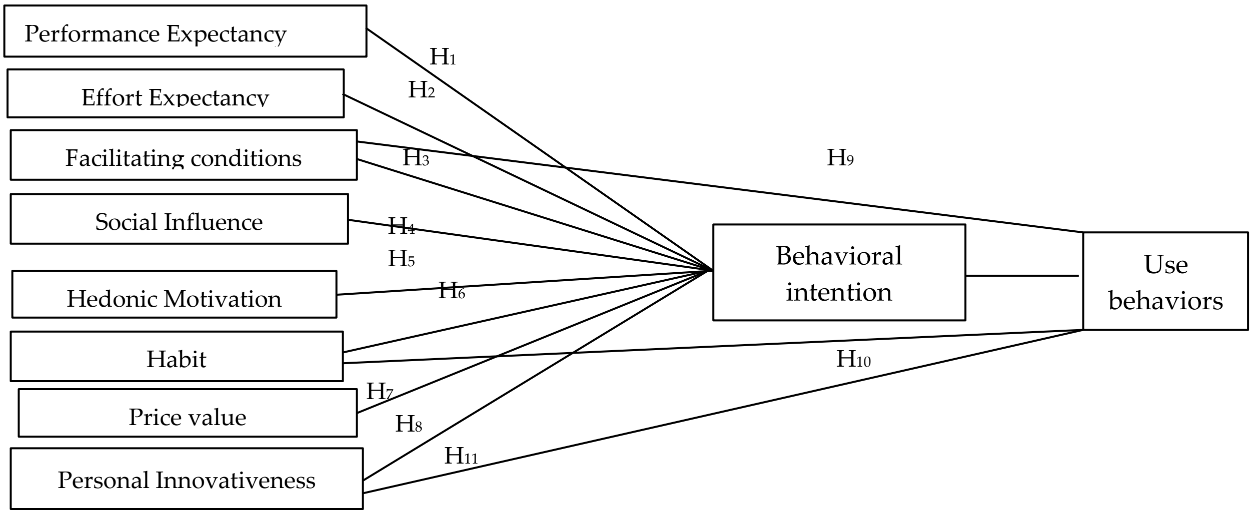

FIGURE 1. Conceptual framework.

VI. RESEARCH METHODOLOGY

1. MEASUREMENTS

The study adopted the quantitative survey approach in order to meet the objective of the present study. In the Figure 1, the dependent variable in the conceptual framework is Use Behavior, while independent variable includes Performance expectancy, effort expectancy, facilitating conditions, social influence, Hedonic motivation, price value, personal innovativeness. The items for Performance expectancy (six items) were adapted [16, 46] and [59] items for Effort expectancy (Four items) were adapted from [16, 46] and [59] items for Facilitating conditions (seven items) were adapted from [16], [46], and [59] , items for social influence (six items) were adapted from [16, 46], and [59], items for Hedonic motivation (six items) were adapted from [16, 46] , and [59] Habit (Six items) were adapted from [16, 46] and [59] Price value (Six items) were adapted from [16, 46], and [59] Personal innovativeness (Six items) [16, 46] and [59] . A five-point Likert scale was used to allow respondents to score their thoughts on each concept, with 1 representing "Strongly Disagree" and 5 representing "Strongly Agree The survey was conducted in Chennai. The questionnaire was circulated through Google form survey blast to individuals who use lending apps. Data were circulated for one month. 210 respondents from lending adoption users. At the same time, previous studies indicate that a sample size of 100 to 200 is typically adequate for path modelling [57].

VII. ANALYSIS AND INTERPRETATION

This section presents the analysis of the collected data and interprets the results in relation to the study objectives. It examines the relationships between key variables and evaluates the findings to provide meaningful insights into the research problem. The interpretation highlights the implications of the results and their relevance to the study context.

Table 1. Reliability Results of the measurement model.

variable	Cronbach's Alpha	Composite Reliability	AVE	Reliability category
Performance expectancy (PE)	0.904	0.930	0.728	0.728
Effort expectancy (EE)	0.928	0.946	0.780	0.780
Social influence (SI)	0.890	0.917	0.690	0.690

Facilitating conditions (FI)	0.895	0.920	0.705	0.705
Hedonic Motivation (HM)	0.918	0.938	0.774	0.755
Price value (PV)	0.920	0.940	0.762	0.762
Habit (HB)	0.898	0.924	0.710	0.710
Personal Innovativeness (PI)	0.892	0.920	0.702	0.702
Behavioral intention (BI)	0.945	0.958	0.825	0.825
Use Behavior (UB)	0.962	0.970	0.870	0.870

(Source: Prepared by Authors, 2025).

Outstanding internal consistency is confirmed by all Cronbach's Alpha values over 0.89. Use Behavior (UB) exhibits the highest dependability (α = 0.962, CR = 0.970), demonstrating extremely good internal consistency. Since every AVE value is more than 0.50, it may be concluded that the constructs adequately account for the variation in their indicators. Although Social Influence (SI) has the lowest AVE (AVE = 0.690), it is still higher above the 0.50 criterion. The use behaviors (UB) have the highest AVE (AVE = 0.870), which suggests good convergent validity.

Table 2. Descriptive statistics.

S. No	Demography variable	Category	Frequency	Percentage (%)
1	Gender	Male	157	51.81
		Female	146	48.19
		Prefer not to say	0	0
		Total	303	100
2	Age	17-22	95	31.35
		23-28	49	16.17
		29-34	24	7.92
		35-40	47	15.51
		41-46	50	16.50
		Above 46	38	12.54
		Total	303	100
3	Employment Status	Employed	160	52.81
		Unemployed	8	2.64
		Student	135	44.55
		Total	303	100
4	Education Level	Higher Education	18	5.94
		Under Graduation	167	55.11
		Post Graduation	109	35.97
		Doctoral or equivalent level	9	2.97
		Total	303	100
5	Marital Status	Married	160	52.81

		Unmarried	143	47.19
		Prefer not to say	0	0
		Total	303	100
6	Monthly Income	Less than Rs.20000	160	52.81
		Rs.20001-40000	143	47.19
		Rs.40001-60000	0	0
		Rs.60001-80000	0	0
		Rs.80001-1,00,000	0	0
		Above Rs.1,00,000	0	0
		Total	303	100

(Source: Prepared by Authors, 2025).

Table 2 shows that the sample size consists of 303 respondents, with nearly equal gender distribution. There were 157 male respondents, or 51.81% of the total, and 146 female respondents, or 48.19%. Among the respondents, none chose "Prefer not to say." Most respondents are between the ages of 17 and 22, accounting for 31.35% of the sample (95 replies). Fifty respondents, or 16.50%, fall into the age group of 41–46. The age range of 29 to 34 is the least represented, with only 7.92% of respondents falling into this category. A broad age range is revealed by the distribution, which includes representation for all age groups from 17 to 46 and beyond. A significant portion of respondents, 52.81% (160 respondents) in the sample, are employed. 44.55% (135 respondents) of the sample are students, which is also a significant portion. Of the responders, just 8 people (2.64%) are unemployed. This implies that employees or students make up the great majority of those polled. While there is diversity in the respondents' educational backgrounds, the majority (55.11%, or 167 respondents) have completed their college degrees. 5.99 percent (18 respondents) have completed higher education, 2.97% (9 respondents) have doctorates or similar degrees, and 35.97% (109 respondents) have postgraduate qualifications. The sample's married and single respondents make up about equal percentages, with 52.81% (160 respondents) being married and 47.19% (143 respondents) being single. Not revealing their marital status was something that every respondent preferred. According to the income distribution, 160 respondents, or 52.81% of the total, make less than Rs. 20,000 a month. 47.19% of the respondents, or 14 other people, earn between Rs. 20,000 and Rs. 40,000. No one responded for income levels above Rs. 40,001. Thus, the majority of the sample appears to be people with low to middle incomes.

Table 3. Convergent validity.

No	Variable	Indicator	Outer Loading	Category
1	Performance Expectancy (PE)	PE1	0.865	Valid
		PE2	0.908	Valid
		PE3	0.860	Valid
		PE4	0.825	Valid
		PE5	0.804	Valid
2	Effort Expectancy (EE)	EE1	0.914	Valid
		EE2	0.928	Valid
		EE3	0.796	Valid
		EE4	0.895	Valid
		EE5	0.900	Valid
3	Social Influence (SI)	SI1	0.835	Valid

		SI2	0.870	Valid
		SI3	0.763	Valid
		SI4	0.808	Valid
		SI5	0.878	Valid
4	Facilitating Conditions (FC)	FC1	0.884	Valid
		FC2	0.840	Valid
		FC3	0.824	Valid
		FC4	0.920	Valid
		FC5	0.730	Valid
5	Hedonic motivation (HM)	HM1	0.748	Valid
		HM2	0.906	Valid
		HM3	0.888	Valid
		HM4	0.925	Valid
		HM5	0.873	Valid
6	Price value (PV)	PV1	0.914	Valid
		PV2	0.975	Valid
		PV3	0.894	Valid
		PV4	0.951	valid
		PV5	0.968	valid
7	Habit (HA)	HA1	0.894	Valid
		HA2	0.818	valid
		HA3	0.788	valid
		HA4	0.906	valid
		HA5	0.876	valid
8	Personal Innovativeness (PI)	PI 1	0.817	Valid
		PI2	0.779	valid
		PI3	0.890	valid
		PI4	0.883	valid
		PI5	0.856	valid
9	Behavioral intention (BI)	BI1	0.930	Valid
		BI2	0.936	valid
		BI3	0.842	valid
		BI4	0.982	valid
		BI5	0.887	valid
10	Use Behavior (UB)	UB1	0.917	Valid
		UB2	0.975	valid
		UB3	0.839	valid
		UB4	0.963	valid
		UB5	0.974	valid

(Source: Prepared by Authors, 2025).

All indicators are valid: Outer loadings > 0.7 (acceptable threshold). Strongest constructs (very high loadings): Price Value (PV), Use Behavior (UB), Behavioral Intention (BI). Moderately strong constructs: Performance Expectancy (PE), Effort Expectancy (EE), Hedonic Motivation (HM), Habit (HA), Personal Innovativeness (PI). Slightly lower but acceptable indicators: SI3 (0.778), FC5 (0.761), HM1 (0.768), PI2 (0.779), HA3 (0.788). The model demonstrates strong convergent validity. All constructs are well-measured by their indicators.

Table 4. Correlation analysis.

Correlations										
	PE	EE	SC	FC	HM	PV	HB	PI	BI	UB
PE	1	.861**	.862**	.838**	.872**	.877**	.863**	.839**	.837**	.863**
EE	.839	1	.883**	.855**	.897**	.905**	.876**	.876**	.883**	.871**
SI	.837	.883**	1	.871**	.877**	.842**	.867**	.867**	.871**	.877**
FC	.838**	.855**	.871**	1	.838**	.847**	.836**	.838**	.838**	.836**
HM	.872**	.897**	.877**	.838**	1	.859**	.860**	.859**	.859**	.860**
PV	.877**	.905**	.842**	.847**	.859**	1	.861**	.861**	.861**	.861**
HB	.863**	.876**	.867**	.836**	.860**	.861**	1	.860**	.870**	.863**
PI	0.68	0.69	0.64	0.67	0.70	0.71	0.72	1	.865**	.867**
BI	0.75	0.76	0.78	0.77	0.75	0.74	0.73	0.78	1	.875**
UB	0.74	0.73	0.68	0.77	0.78	0.73	0.74	0.75	0.73	1

**. Correlation is significant at the 0.01 level (2-tailed).

(Source: Prepared by Authors, 2025).

The Pearson correlation coefficients among the ten UTAUT3 constructs PE, EE, SI, FC, HM, PV, HB, PI, BI, and UB demonstrate the strength and direction of linear relationships between these variables. All correlations are positive, ranging mostly between 0.68 and 0.91, which reflects strong to very strong positive associations. All relationships marked with ** are statistically significant at the 0.01 level (2-tailed), which means they are unlikely to occur by chance, providing solid statistical evidence for the relationships. Strong positive correlations are observed across nearly all variable pairs:

- PE and EE (.861**), PE and HM (.872**), and EE and PV (.905**) indicate that as users' expectations of usefulness and ease increase, their enjoyment and perceived value also increase.
- EE and SI (.883**), SI and HM (.877**), and FC and PV (.847**) suggest mutual reinforcement among social, technical, and motivational factors.

Habit (HB) shows strong correlations with:

- PV (.861**), HM (.860**), and PI (.860**), implying that regular use habits are associated with enjoyment, value perception, and innovativeness.

Behavioral Intention (BI) correlates strongly with:

- PI (.865**), HB (.870**), and HM (.859**), highlighting that personal motivation, habits, and innovativeness are key predictors of intent.

Use Behavior (UB) also has high correlations with:

- HM (.860**), HB (.863**), and BI (.875**), suggesting that actual usage behavior is strongly linked with intention and habitual engagement.

All variables are positively related, meaning they rise together no inverse (negative) relationships are observed.

Table 5. Regression analysis.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.914a	.836	.819	2.245	1.709

a Predictors: (Constant), PE, EE, SI, FC, HM, PV, HB, PI, BI

b Dependent Variable: UB

(Source: Prepared by Authors, 2025).

When assessing the degree to which independent variables impact dependent variables, the R-squared value is employed. R-squared was a crucial parameter in regression since it indicates the degree to which independent factors affect dependent variables. The adjusted R squared illustrates the model's cross-validation and generalization ability. Based on Table 5, the R-squared value was 0.836, indicating that all of the independent factors together accounted for 83.6% of the variability in the dependent variable. Utilizing Durbin-Watson, one can ascertain the autocorrelation between variables. For reasonably normal values [58] proposed that the Durbin-Watson value should fall between 1.5 and 2.5. It was evident from the research value of 1.709 that the above Table 5 did not exhibit auto-correlation.

Table 6. ANOVA table.

Anova						
	Model	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1539.541	6	256.590	50.896	.000[b]
	Residual	302.489	60	5.041		
	Total	1842.030	66			

a. Dependent Variable: UB
b. Predictors: (Constant), PE, EE, FC, SI, HM, HB, PV, PI, BI

(Source: Prepared by Authors, 2025).

The predictors are responsible for the variance in UB, as indicated by the Regression Sum of Squares (1539.541). Regarding UB, the unexplained variance is displayed by the residual sum of squares (302.489). The F-statistic results are 50.896, $p < 0.001$. The highly significant result (Sig. = 0.000), which shows that the predictors collectively explain the variance in UB, suggests that the entire model fits the data.

Table 7. Coefficient table.

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.375	1.112		-.337	.737
	PE	.203	.133	.200	1.529	.132
	EE	.202	.159	.199	1.273	.208
	SI	.239	.154	.213	1.556	.125
	FC	.089	.133	.081	.672	.504
	HM	.133	.155	.119	.861	.393
	PV	.163	.147	.156	1.111	.271
	HB	.118	.140	.110	.843	.402
	PI	.145	.150	.134	.967	.336
	BI	.228	.125	.216	1.824	.072

a. Dependent Variable: UB

(Source: Prepared by Authors, 2025).

Table 8 Unstandardized and standardized beta coefficients along with their respective t values were provided. The Regression equation derived from the above table is UB = –0.375 + 0.203(PE) + 0.202(EE) + 0.239(SI) + 0.089(FC) + 0.133(HM) + 0.163(PV) + 0.118(HA) + 0.145(PI) + 0.228(BI). Although it is only getting close to significance (p = 0.072), Behavioral Intention (BI) has the greatest impact on Use Behavior (UB), with a beta of 0.216.Other factors with beta values between 0.199and0.213,including Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI), also show moderate influence .Hedonic Motivation (HM) and Facilitating Conditions (FC) had lesser beta values (0.081 and 0.119, respectively), which suggests that they have less of an impact. Habit (HA) and Personal Innovativeness (PI) had beta values of 0.110 and 0.134, respectively, indicating a slight impact.

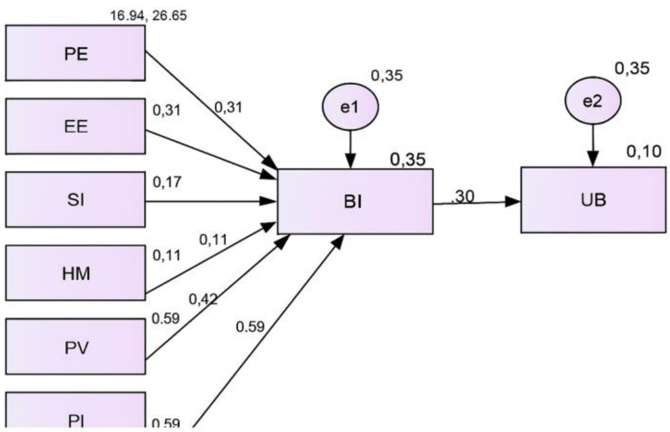

FIGURE 2. Path analysis.

Table 8. Regression weights: (group number 1 - default model).

			Estimate	S.E.	C.R.	P
BI	<---	PE	0.060	.045	7.032	***
BI	<---	EE	0.065	.049	-1.206	.228
BI	<---	FC	0.085	.049	3.546	***
BI	<---	SC	0.070	.045	10.946	***
BI	<---	HM	0.070	.049	.901	.368
BI	<---	PV	0.072	.090	9.970	***
BI	<---	HB	0.068	.049	.901	***
BI	<---	PI	0.066	.045	7.032	***
UB	<---	BI	0.090	.049	3.546	***

Table 8 displays the regression weights from the structural model, showing how the UTAUT3 components relate to users' Use Behavior (UB) and Behavioral Intention (BI). Performance Expectancy (PE), Facilitating Conditions (FC), Social Influence (SC), Price Value (PV), Habit (HB), and Personal Innovativeness (PI) all affect behavioral intention in a positive and statistically significant way, according to the results ($p < .001$). According to these findings, people are more likely to plan to use digital loan services if they believe the technology is helpful, backed by a strong infrastructure, respected by society, affordable, ingrained in their routines, and compatible with their own openness to trying new things. Hedonic Motivation (HM) and Effort Expectancy (EE), on the other hand, had non-significant effects on behavioral intention, suggesting that user-friendliness and enjoyment do not significantly influence intention in this situation. Further supporting its key mediating function in forecasting actual system use is the positive and considerable impact that Behavioral Intention (BI) itself has on Use Behavior (UB). These findings highlight how crucial performance-oriented, social, and motivational characteristics are in determining user adoption and sustained usage of digital lending technologies, particularly Habit and Personal Innovativeness.

VIII. DISCUSSION

1. THE INFLUENCE OF PERFORMANCE EXPECTANCY ON BEHAVIOURAL INTENTION

The results show that behavioral intention to use digital lending services is positively and significantly influenced by performance expectancy. [16] found that performance anticipation was a crucial component of technology adoption across a range of digital platforms. This is consistent with their earlier findings. Both [49], who looked at behavioral intention in Malaysian educational technology usage, and [53], who looked at user behavior in virtual learning environments, corroborate the current findings. According to these similarities, consumers are more likely to embrace digital lending technologies when they see observable performance advantages like effectiveness, ease, or financial accessibility.

2. THE INFLUENCE OF EFFORT EXPECTANCY ON BEHAVIOURAL INTENTION

In contrast to certain previous research, the analysis shows that effort expectancy has no discernible effect on behavioral intention in this situation. [52] found comparable results among Indonesian mobile banking customers, which is in line with our research. The findings imply that people accustomed to digital platforms no longer consider ease of use to be a top priority. Particularly in urban locations like Chennai, people may place a higher value on functional advantages over usability as digital literacy rises.

3. THE INFLUENCE OF SOCIAL INFLUENCE ON BEHAVIOURAL INTENTION

Social influence does not significantly alter behavioral intention when it comes to the adoption of digital lending services, according to the study. The findings by [52] and [49] are supported by this, suggesting that peer opinions or social standards may have little effect on digital financial behavior, especially in situations that are highly digitalized or individualistic. Instead, then depending on the opinions of others, users could rely more on their own assessments.

4. THE INFLUENCE OF FACILITATING CONDITIONS ON BEHAVIOURAL INTENTION

The analysis also shows that facilitating conditions do not significantly influence behavioral intention. This finding is consistent with research by [50] and internal IT research at PT Kereta Api Indonesia. Despite the availability of technical and organizational support, such conditions alone may not be sufficient to shape user intention unless coupled with motivational or experiential factors.

5. THE INFLUENCE OF HEDONIC MOTIVATION ON BEHAVIOURAL INTENTION

The study concludes that behavioral intention is not much impacted by hedonic incentive. This is consistent with the findings of [54], who found comparable outcomes in the banking industry of Lebanon. The implication is that consumers view digital lending more as a service driven by utility than as one that is connected to pleasure or delight.

6. THE INFLUENCE OF PRICE VALUE ON BEHAVIOURAL INTENTION

Price value appears to have no bearing on behavioral intention toward the adoption of digital lending, according to the data. Studies [45] and [52] found that the cost of using these services is not a significant factor of behavioral intention, which is consistent with this result. Consumers may believe that digital lending platforms provide non-monetary benefits like convenience and time savings, which would make price considerations less important.

7. THE INFLUENCE OF HABIT ON BEHAVIOURAL INTENTION

According to the study, habit significantly and favorably influences behavioral intention. According to [16] and [49], this emphasizes how past usage and repetition influence present and future goals. Habitual behavior strengthens users' inclination to stick with digital lending platforms as they get more comfortable with them.

8. THE INFLUENCE OF PERSONAL INNOVATIVENESS ON BEHAVIOURAL INTENTION

According to the research, behavioral intention is strongly and favorably influenced by personal innovativeness. The results of [54] and [49] are supported by this, indicating that those who are more willing to try new technologies are more likely to use digital lending platforms.

9. THE INFLUENCE OF FACILITATING CONDITIONS ON USE BEHAVIOUR

Facilitating conditions are shown to have a favorable and noteworthy influence on actual use behavior, in contrast to their effect on intention. This finding aligns with the findings of [18], who emphasized the significance of infrastructure support in encouraging the usage of technology. Users are more likely to act on their intentions when they have access to sufficient resources and assistance.

IX. UTAUT-3 ANALYSIS OF MOBILE LENDING USE AND INTENTION

1. THE INFLUENCE OF HABIT ON USE BEHAVIOUR

Additionally, habit has a good and significant impact on usage behavior, according to the investigation. Findings by [16] and [49] are supported by this, highlighting the fact that regular use and familiarity encourage sustained use of digital lending services.

2. THE INFLUENCE OF PERSONAL INNOVATIVENESS ON USE BEHAVIOUR

Use behavior is not greatly influenced by personal innovativeness, in contrast to its impact on intention. This result validates the findings of [53], who observed that although inventive people may start using it, actual continuing behavior is more driven by contextual factors and real-world experience.

3. THE INFLUENCE OF BEHAVIOURAL INTENTION ON USE BEHAVIOUR

Digital lending adoption use behavior is positively and significantly influenced by behavioral intention, according to the study. This finding supports earlier studies by [49] and [56] confirming the central tenet of the UTAUT-3 model that intention is a reliable indicator of actual use.

4. DOMINANT VARIABLES

Perceived usefulness is crucial for the adoption of digital loans, as performance expectancy is the most important factor influencing behavioral intention among all examined factors. Behavioral intention is still a key factor in determining actual usage, but habit also plays a large role in both behavioral intention and use behavior. These results highlight how user behavior in scenarios involving digital financial technology is based on functional value, past experience, and intention.

X. CONCLUSION

The research findings, hypothesis testing, and analysis carried out in this study allow for the following deductions to be made about the Chennai region's adoption of digital lending services: Personal innovativeness, performance expectations, and habits all significantly and favorably affect behavioral intention to use digital lending services in Chennai. According to this, people are more likely to utilize digital lending platforms if they believe they are advantageous, are comfortable with digital financial services, and are willing to try new technologies. However, behavioral intention is not significantly influenced by effort expectancy, social influence, facilitating conditions, hedonic motivation, or price value. This suggests that easy-to-use features, peer pressure, enjoyment, support infrastructure, and cost are less important for users in this region during the intention-formation stage. The way people use digital loan services is positively and significantly impacted by enabling factors, habit, and behavioral intention. Accordingly, sustained use is contingent upon consumers' prior experiences, the infrastructure or support that is in place, and the degree to which they intend to use these services. However, personal innovativeness has no discernible effect on use behavior, suggesting that while innovative users are open to trying digital lending, their sustained use is contingent upon variables other than personal characteristics. The factors that have the biggest effects on behavioral intention and use behavior are the most prevalent in this study. Habit strongly influences both behavioral intention and actual use behavior, although performance expectancy is the most important element influencing behavioral intention. A significant factor in determining whether customers really use digital loan services is behavioral intention itself.

1. *LIMITATIONS*

Despite the insightful information this study provided, a number of limitations should be noted. First off, the study was limited to the Chennai area, which would have limited the findings' applicability to other cities or rural areas with varying degrees of financial literacy, internet infrastructure, or socioeconomic characteristics. Furthermore, the research's cross-sectional design records user attitudes and actions at a certain moment in time, which makes it challenging to assess how adoption or usage patterns have changed over time. Third, the research only used self-reported data, which could be skewed by response biases such false memory or social desirability. Furthermore, no moderating variables that could provide more in-depth understanding of user behavior, such as age, gender, income, or digital literacy, were included in this study. Finally, although while the study took into account generic digital lending platforms, it did not distinguish between other kinds of platforms, such as peer-to-peer lending, app-based microloans, or traditional bank-led digital lending, which might have had varying effects on user experiences and views.

2. *THEORETICAL IMPLICATIONS*

This study validates and expands the UTAUT-3 paradigm in the context of digital lending services in India, adding to the expanding corpus of research on technology adoption. The results validate the theory's central claim that habit and performance expectancy are powerful indicators of technology adoption. By highlighting the role that individual traits play in shaping adoption behavior, the inclusion of personal innovativeness also contributes theoretical value. Notably, the lack of significance for pricing value, social impact, and effort expectancy casts doubt on their universal applicability and raises the possibility that these could differ depending on social exposure, digital maturity, and financial literacy levels. Thus, the research highlights the necessity of contextualizing theoretical models such as UTAUT-3, especially in developing economies. Furthermore, the lack of moderating variables in this study provides a clear validation of the direct paths in the UTAUT-3 framework, enabling the addition of moderators (like age, gender, or digital literacy) for a more thorough understanding in subsequent research.

3. *PRACTICAL* IMPLICATIONS

The results provide useful recommendations for fintech businesses, digital lenders, and legislators. The significant impact of performance expectations suggests that platforms should concentrate on highlighting the obvious, observable advantages of using digital lending services, like expediency, ease of use, and transparency in approvals. Habit's effect highlights the value of user retention tactics, such as gamified financial planning features, regular involvement through notifications, and easy app design, which promote recurring use. Personal innovativeness influences initial adoption but not persistent use, so platforms should simultaneously improve loyalty-building features and target early adopters. From the standpoint of policy, the findings highlight the necessity of digital financial education programs that guarantee safe use in addition to encouraging uptake. To improve digital literacy, borrowing awareness, and debt management particularly for younger or novice users' government organizations and financial authorities should work with fintech companies.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Conceptualization, R. B. and V. K.; methodology, R. B. and V. K.; software, R. B.; validation, V. K.; formal analysis, R. B.; resources, V. K.; data curation, R. B.; writing—original draft preparation, R. B.; writing—review and editing, V. K.; visualization, R. B.; supervision, V. K.; project administration, V. K.; funding acquisition, R.

B. All authors have read and agreed to the published version of the manuscript and contributed equally to the development and planning of the study.

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Data are available from the authors upon request.

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