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Role of Gamification and Perceived Value on Consumers' Behavioural Intention to Use Buy-Now, Pay-Later (BNPL) Services through the Extended Tam Model

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ABSTRACT

The research examines the factors that influence consumers' behavioral intention (BI) to utilize Buy-Now, Pay-Later (BNPL) services, with the addition of two outside variables, gamification (GM) and perceived value (PV), in the technology acceptance model (TAM). The authors adopted a quantitative deductive method, conducting an online survey of 280 university students in Chennai. The authors used partial least squares structural equation modelling (PLS-SEM) to assess the ten hypotheses about the relationships of the variables using SmartPLS 4. The results showed that all ten hypotheses were positive, indicating the model's robustness. GM significantly impacted PV ($\beta = 0.577$, $t = 13.602$, $P < 0.001$), attitude (ATT) ($\beta = 0.241$, $t = 4.284$, $P < 0.001$), and BI ($\beta = 0.134$, $t = 2.073$, $P < 0.05$), demonstrating GM's motivational aspect of BNPL services. In addition, perceived ease of use (PEU) significantly impacted perceived usefulness (PU) ($\beta = 0.491$, $t = 11.201$, $P < 0.001$) and ATT ($\beta = 0.309$, $t = 5.177$, $P < 0.001$), while PV had a significant impact on BI ($\beta = 0.188$, $t = 2.980$, $P < 0.01$). The model was able to explain 43.5 of % variance of behavioral intention (BI) and 28.9 of % variance of actual usage (AU), suggesting reasonable explanatory and predictive validity. This study contributes to the fintech adoption literature by adding experiential and psychological dimensions to the TAM and has practical relevance for practitioners seeking to build interesting, value-oriented, and socially responsible BNPL services targeted at younger consumers.

Keywords: Buy-Now, Pay-Later, Gamification, Perceived Value, Technology Acceptance Model, Fintech Adoption, India
JEL Classifications: G21, G23, D91, O33, M31

1. INTRODUCTION

The developments in technology have radically altered consumer purchasing behavior over time (Stankevich, 2017). Economic digitalization has also been accelerating, particularly since COVID-19. The pandemic made people less inclined to handle cash due to the potential for physical contact and the transmission of the virus when handling it. People became accustomed to cashless transactions using digital payments, and it has become a large part of consumer purchasing decisions, especially with countries advocating for cashless policies and promoting a range of cashless digital payment options (Santosa et al., 2021; Teng and Khong, 2021; Viet Tam et al., 2024). Digital payments and e-wallets are having an effect, and e-wallets are being enhanced with features that make transactions quicker and easier for consumers. One of these enhancements that has presented itself has been the introduction of options such as "buy now, pay later" procedures (Bian et al., 2023). "Buy now, pay later" plans are similar to credit cards in that consumers can make purchases immediately and then pay the organization or retailer in regular installments (Cook et al., 2023). A fixed repayment period is established for a "buy now, pay later" option and is not a revolving line of credit like a credit card (Kumar et al., 2024). Innovative applications, such as digital wallets, buy now pay later, and A2A in real time, have substantially changed consumer payment methods. Global spending with digital payment methods, either face-to-face or online, will rise almost elevenfold, from $1.7 trillion in 2014 to $18.7 trillion in 2024. By the year 2030, it is anticipated that the value of digital payment will exceed $33.5 trillion, with the subcategory of BNPL appearing to be one of the fastest expanding, with estimates of rising to $342 billion for BNPL from $2.2 billion in 2014 (Worldpay, 2025). Prior research has considered the negative aspects of BNPL (Schomburgk and Hoffman, 2023; Relja et al., 2024; Gerrans et al., 2021; Powell et al., 2023; Aalders, 2022). Additionally, in the past few years, researchers have considered factors that shape consumers' perceptions of BNPL (Juita et al., 2024). For example, Behera and Dadra (2024) indicated that affordability, flexibility, structural assurance, and perceived usefulness (PU) influence consumers' attitudes toward using BNPL services. GM is described by Gupta et al. (2024) as the application of game-design elements; this can include points, badges, leaderboards, tasks, and levels added to a non-game context. GM can involve elements of progressive challenges to engage users with reward unlocking, leaderboards showing performance ranking to promote competition with others, and redeemable points to promote transactions (Sharma et al., 2024). GM increases user motivation and brand attachment in ways that reward an action or interaction in various forms, including, but not limited to, purchasing or engagement with the application (Sharma et al., 2024).

1.1. Research Gap

The present value in BNPL positively impacts benefits like ease, convenience, and usability, whereas the interest costs that must be paid can influence purchasing behavior (Schomburgk and Hoffman, 2023). There is a crucial gap in research, as the reason for the adoption of technology is PV (Galetsi et al., 2023; Viet Tam et al., 2024). How PV affects consumers' BNPL adoption needs to be examined. BNPL services employ gamified and social media-like features to establish frictionless user interfaces that are reportedly tailored to the manner in which young individuals interact with online and digital spaces, thereby generating financialized subjectivities (Threadgold et al., 2024). Literature is scarce on the PV and GM, both effects of BNPL; we identified two research-significant gaps. As a result, the following research questions are the focus of this study:

- RQ_1: What effect does GM have on a consumer's use of BNPL services?
- RQ_2: What effect does PV have on a consumer's use of BNPL services?

To investigate these research questions, the study adopts the Study TAM from Davis (1989), as it is commonly used in the cited literature, adapting it to technology adoption. Specifically, TAM holds PEU and PU as fundamental reasons technology users will intend to adopt new technologies (Davis, 1989). The antecedents PU and PU remain valid to account for adopting digital payment methods: Digital lending platforms or BNPL methods (Hidayat et al., 2024; Syifa et al., 2025; Yadav and Shanmugam, 2024; Putri et al., 2023). Nevertheless, the perceived usefulness (PU) from the technology acceptance model (TAM) may not address the psychological and experiential aspects of Buy Now Pay Later (BNPL) platforms; therefore, this study includes two additional external variables: Goal motivation (GM) and perceived value (PV) related to PU. GM remains an account for this effect on the motivation or engagement of users to solve complex problems, specific actions, or just enjoying (Tobon et al., 2020). Hegawan et al. (2023) observe a strong effect of the usefulness of PayLater/BNPL for PV on customer satisfaction, post-purchase intention, or impulsive buying behavior. This research will extend TAM with GM and PV to meet the prospective influences defining appropriate and comprehensive understandings of users' intentions to use BNPL.

1.2. Objectives of the Study

1. To study the influence of GM on consumers' PV, PU, and BI to adopt BNPL services, especially among university students
2. To examine how PV affects university students' BI to use BNPL
3. To analyze the impact of PEU on PU and ATT towards BNPL services, especially among university students
4. To evaluate the effect of PU on university students' ATT and their BI
5. To examine the impact of ATT on university students' BI to use BNPL services
6. To evaluate the correlation between university students' BI and their AU of BNPL services
7. To provide managerial recommendations for fintech companies to expand BNPL usage through gamification and value propositions.

1.3. Contribution of the Study

This research enhances the existing TAM by encompassing GM and PV as external variables, developing a more comprehensive approach for understanding BNPL adoption, particularly for students in universities. The research contributes to both fintech firms and consumer behavior literature through emphasizing experiential dimensions, such as PV, as well as psychological components, such as GM. It contributes to the growing stream of research on gamified financial services that show how game-like elements may be useful for enhancing consumer motivation and PU toward fintech platforms. In addition, the results of this study present practical opportunities for fintech firms and BNPL providers to improve user engagement with reward-based user interfaces that may enhance consumer loyalty. By appreciating PV, companies can successfully strike a balance between perceived benefits and convenience in order to facilitate responsible usage among university students. The research also provides insights to policymakers and regulators who are identifying behavioral and psychological adoption happenstance. Finally, this research provides robust measurement, and a structural model serves as an empirical basis for future advanced research studying digital finance, consumer engagement, and technology adoption.

The remainder of this paper will proceed as follows. Section 2 examines the literature and BNPL box services, TAM, GM, and PV to develop hypotheses for the study. Section 3 will then outline the methodology, which includes research design, sampling, data collection, and analysis using PLS-SEM. Section 4 will present and discuss research findings, including assessments of both measurement and structural models. Discussion of the research findings with respect to theory and practice can be found in Section 5. Finally, Section 6 concludes the research study, providing a review of limitations and recommendations for future research.

2. REVIEW OF LITERATURE AND DEVELOPMENT OF HYPOTHESES

2.1. Buy Now Pay Later

"Consumer preferences" with respect to "payment methods" have changed significantly in recent years (Filotto et al., 2024). According to Kumar et al. (2024), BNPL users spend 6.42% more than non-BNPL users. The use of BNPL as a "payment option" in an online retail setting enables direct consumer financing at the moment of sale. Customer's financial demands are successfully met by this integration at the point of decision-making, resulting in a flawless shopping experience (Sieber and Guibaud, 2022). A distinctive FinTech service that offers flexible credit support for consumers' retail purchases, e-pay later services, or BNPL solutions is better defined as a program with an initial payment and multiple monthly payments (Guttman-Kenney et al., 2023). This service is often offered as a digital invoice by financial companies working in conjunction with e-commerce platforms to enable clients to delay payment until sometime after their purchases, typically after the items have been delivered. BNPL is a new means of credit that allows consumers to use a mobile application to make purchases and pay later online (Powell et al., 2023). Therefore, this research aims to provide high-quality input data for various options to study BNPL and consumer decision-making in Chennai, as this dataset has rich data and demographic information that provides our study with a complete and segmented dataset for analysis and testing based on consumer group characteristics, such as age, gender, education level, etc.

2.2. TAM

Numerous studies explaining the adoption of technology have been based on Ajzen and Fishbein's original "theory of reasoned action" (TRA). Ajzen (1985) developed the "theory of planned behavior" (TPB) in response to TRA, which improved the model even more. The creation of the TAM and its later versions (Ajzen, 1985; Venkatesh et al., 2003) are just a few examples of the extensive use of these theories in the study. Davis (1989) was the one who first developed the TAM, which has since become a well-known paradigm for analyzing how external factors affect people's ATTs, beliefs, and intentions around technology adoption. Figure 1 presents the TAM model, which Davis (1989) developed. The TAM purpose is to understand people's perceptions and reactions to technology (positive and negative). The TAM model provides a richer description of beliefs based on PU and PEU through characteristics that influence memory and cognitive processing. People's behavior is influenced by their BIs, ATTs, beliefs about the technology's usefulness (PU), and beliefs about human-computer interaction PEU when using that technology (Davis, 1989). According to the TAM model, although both the TRA and TAM models consider BIs, TAM presents additional factors that influence technology usage (ATT, PU, PEU) relevant to technology usage. TAM expands on the TRA framework while providing more understanding of factors that influence ATT and, when abridged into cognition, intention regarding the use of technology. The TAM framework offers a deeper comprehension of how these cognitive factors work by expanding the TRA framework and contributing to technology adoption decisions and rejection, which could ultimately guide researchers and practitioners in the development of educational and user-centered design plans to promote the adoption and usability of technology.

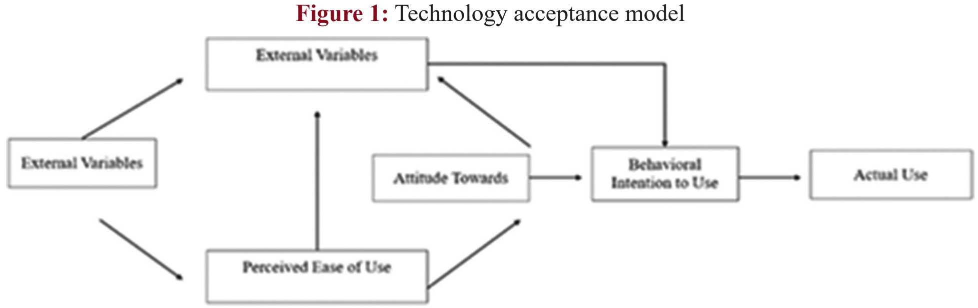
2.3. Cost-Benefit Theory (CBT) and Perceived Value

CBT was introduced by Drèze and Stern (1987). CBT is a human strategy that aims to maximize benefits and minimize downsides in a discrete manner to make decisions relating to prior behavior. According to studies by Lin et al. (2020) and Lin and Lu (2015), consumers assess the advantages and disadvantages of dealing with a product or service, leading to the conclusion that they would consider the overall value of the PV. Both actual and intangible expenses are taken into account when people are making judgments about what they should accomplish. Comparing the cost and benefits of a certain technology or information system also affects willingness to embrace it. Firms can mitigate performance risk and financial risk by increasing perceived value; firms have incentives to raise consumer perceptions of quality through brand name, store, country of origin, and price (Agarwal and Teas, 2001).

2.3.1. Research in BNPL acceptance model

Vikas Sharma et al. (2024) employ the SERVQUAL model as an external variable and extend the technology acceptance model (TAM) to assess how service quality impacts the usage of FinTech services, finding that service quality positively affects perceived usefulness (PU) and perceived ease of use (PEU) for FinTech payment services. Syifa et al. (2025) studied the factors that influence the adoption of BNPL with the use of TAM2, which consists of social and cognitive factors, and the findings indicate that subjective norm, job relevance, output quality, result demonstrability, PEU, and PU all significantly influence ATTs and intentions. Hidayat et al. (2024) uses TAM and the Theory of Planned Behavior (TPB), two frameworks, to assess intention to use BNPL resulting from adoption, and intention was supported by perceived risk, trust, and subjective norm (Table 1).

Figure 1: Technology acceptance model



Source: Adapted from (Davis 1989)

2.4. Hypotheses Development

In this investigation, our goal is to look into the variables that affect BNPL players' adoption. While incorporating critical components of the original TAM model, we also broaden its scope by incorporating additional components, including PV and GM. Previous research has demonstrated the importance of these factors in shaping the adoption of technology (Marangunić and Granić, 2015). A path diagram is presented to illustrate the connections between the suggested variables, and the SEM analysis technique is employed to analyze them. Using this approach, we can graphically depict the relationships between the different variables and examine how they affect the uptake of BNPL (Figure 2).

2.4.1. Attitude - ATT

The term "ATT towards BNPL" describes users' positive or negative feelings about using it. Ajzen and Fishbein (1977) define ATT as the degree to which people view the performance of specific behavior favourably or unfavourably. According to Davis (1989), opinions regarding digital banking are impacted by perceived utility and perceived usability. Customers have positive ATTs regarding the purchase intention to use internet technology, according to Lai and Li (2005). Thus, this research suggests that:

- H_1: BNPL users' BI is positively impacted by ATT.

2.4.2. Perceived usefulness - PU

PU is the subjective likelihood that utilizing a specific application in an organizational setting will enhance an individual's performance at work, according to Davis (1989). Numerous studies have shown that perceived usefulness is a significant predictor of BIs (Davis, 1989; Venkatesh et al., 2012). According to the current study, PU's adoption and use of BNPL will benefit both the ATT and the BI. Given this information, we hypothesize the following:

- H_2: PU has a positive impact on BNPL users' BI.

In addition to its impact on BI, Davis (1989) demonstrated that PU has an impact on ATTs' use of technology. This leads to the establishment of the following hypothesis:

- H_3: BNPL users' ATT is positively impacted by PU.

2.4.3. Perceived ease of use - PEU

With regards to this study, we propose that the ATT towards BNPL and PU will be positively affected by the PEU. Davis (1989) and Venkatesh et al. (2012) have previously examined two dimensions of technology acceptance, one of which is PEU. PEU suggests that users believe the technology does not need high levels of effort to use (Davis, 1989). In this context, we assume that if consumers believe BNPL is easy to use, this will increase the possibility that they will use the advantages of BNPL. With this phenomenon in mind, we propose the following hypothesis:

- H_4: PEU positively affects PU for using BNPL services
- H_5: PEU positively influences ATT to use BNPL services.

2.4.4. Perceived value (PV)

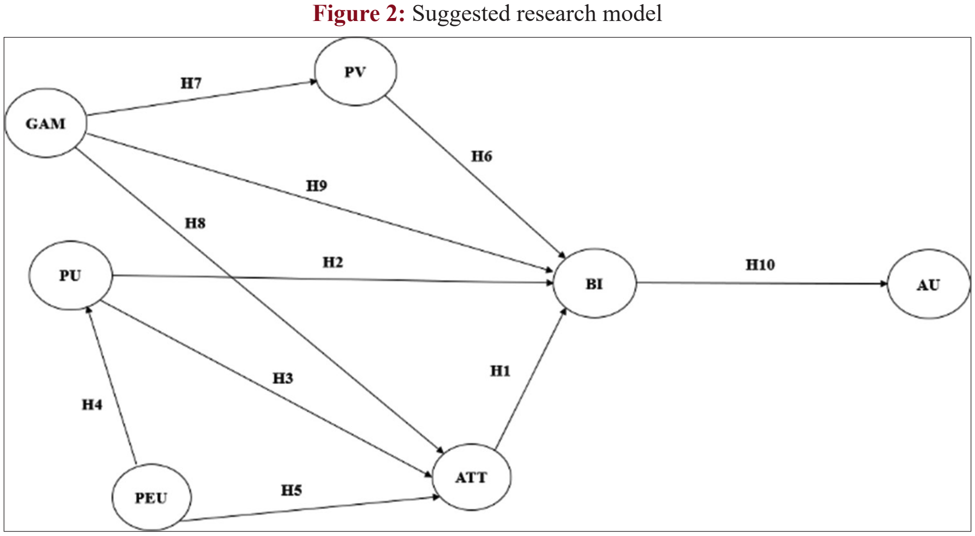
According to our research paradigm, PV is thought to be a major intervening factor. A person's overall evaluation of a product or service's usefulness is based on a comparison of perceived benefits (utility) and PU (usually financial considerations) is known as PV (Zeithaml et al., 1988; Yang et al., 2016). It has been shown by Lin et al. (2020) that users' intention to use mobile payment services is positively influenced by value perception. Previous studies indicate that people perceive benefits in terms of purchasing costs or the expenses of utilizing the application or system, and they are more likely to adopt the new technologies (Hamouda, 2019; Xiong, 2013). Therefore, it can be concluded that if users are more likely to embrace and use BNPL, if they think it has advantages. The following theories regarding the PV factor were developed based on findings from the literature:

- H_6: PV positively affects BNPL users' BI.

2.4.5. Gamification-(GM)

The gamification strategies have a significant contribution to direct and positive effects on users' engagement in e-commerce (García-Jurado et al., 2021). GM seeks to establish a connection between utility and engagement; findings suggest GM is influential in crowdsourcing platforms (Hernandez-Ortega et al., 2017). A study also indicated that GM in digital spaces enhances the PV of consumers of digital banking services (Ciunova-Shuleska et al., 2022). In a study of social media, Aydin (2015) shows the ways in

Figure 2: Suggested research model



Source: Author's own design

Table 1: An overview of earlier research on BNPL studies

Author (s) and year	Context	Variables and model used	Findings
Raj et al. (2025)	BNPL	UTAUT2+Perceived risk+Perceived benefits	Social influence, perceived benefit, and effort expectancy were the most significant factors affecting the behavior of BNPL
Raj et al. (2024)	BNPL	Materialism, impulsive buying, and compulsive buying	Materialism influences BNPL usage and encourages impulse buying, resulting in dangerous buying behaviors.
Hui et al. (2025)	BNPL	TPB	Behaviors are significantly predicted by intention to use BNPL services. The link between subjective norms and behavioral intentions is significantly moderated by perceived convenience.
Mat et al. (2025)	BNPL	TAM+UTAUT	The intention to use BNPL services significantly correlates with PU, FL, and SI.
Sahni (2025)	BNPL	Convenience and ease of access, zero or low-interest payment plans, trust in digital platforms, consumer psychology, marketing strategies, financial flexibility	Consumer psychology and Marketing strategies play a dominant role in consumer behavior using BNPL services.
Ahmad et al. (2025)	BNPL	TAM+TPB	Consumer behavior and financial flexibility have a significant relationship with the usage of BNPL
Llanto (2025)	BNPL	TAM+UTAUT	PU, PEOU influences BNPL adoption intentions.
Hoo et al., 2024	BNPL	UTAUT2+Perceived risk+Perceived benefits	User-friendliness has a positive impact on materialism, SI, and the intention to use BNPL.

which GM motivates users and produces feelings of excitement and fun, thus motivating their ATT and level of use. Baptista and Oliveria (2017) showed that GM features positively influenced user usage behavior, allowing users to learn new knowledge of cyber safety through the speed and engagement of games (Chopdar & Balakrishnan, 2020).

- H_7: GM positively influences the PV of BNPL users
- H_8: GM positively influences the ATT toward BNPL users
- H_9: GM positively influences the BI of BNPL users.

2.4.6. Behavioral intention - (BI)

"BI" refers to a person's willingness to engage in action without requiring confirmation from the outside. The purpose of this study, BI, is the user's intention to make continued use of BNPL (Ajzen and Fishbein, 1977). Past research in consumer psychology and behavior research has explored the impact of intentions on actual behavior (Ajzen, 1991). Studies have found that the BI performed a direct and significant effect on actual use (AU) of the e-learning system (Alsabawy et al., 2016; Al-Gahtani, 2016). The BI has a direct relationship to affect the user's actual use (Kimiagari and Baei, 2022). Accordingly, the research will suggest the following theories:

- H_{10}: AU is positively impacted by BI used by BNPL users.

3. RESEARCH METHODOLOGY

3.1. Design and Approach

The research utilizes a quantitative approach to gather numerical data by means of standardized questionnaires, and to test the hypotheses that were developed, statistical methods (such as SEM) were used. The study utilizes a descriptive approach to express university students' perceptions, knowledge, and BIs about the usage of BNPL. It inspects cause-and-effect relationships between constructs GM, PV, PU, PEU, ATT, BI, and AU.

The study adopts a deductive research approach; deduction is based on the foundation principles of Aristotelian logic, the linchpin of the scientific method, which involves acquiring knowledge through the testing of falsifiable hypotheses (Popper, 1959). This study integrates TAM (Davis, 1989), this framework provides a theoretical base that explains BNPL adoption, especially among university students. The study was extended by including GM and PV as additional determinants to the specific hypotheses.

3.2. Measurement Items

The data from BNPL users was collected using an adapted structured questionnaire in this investigation. Two parts made up the questionnaires. Section A was used to measure respondents' (i.e., BNPL customers) sociodemographic profile (Table 2). Section B measured consumer responses to BNPL with responses over items using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). The appendix provides all items that were used to measure the data collection. The measurement criteria of "PEU", PU", "ATT" were taken from (Davis, 1989); "GM" from (García-Jurado et al., 2021); "PV" from (Lin et al., 2020) and (Xiong, 2013); "BI" and "AU" from (Ajzen and Fishbein, 1977); (Ajzen, 1991) and (Kimiagari and Baei, 2022).

3.3. Sample and Data

An online survey methodology was implemented to gather data. Due to its cost-effective and timely coverage of geographical regions, the online survey was chosen (Raj et al., 2022). (Purohit et al., 2022) and (Raj et al., 2023) have applied this survey methodology to collect data in comparable contexts. To assess item clarity, survey flow, and psychometric properties, a pilot survey was conducted in June 2025 involving 54 respondents - including four marketing assistant professors, postdoctoral research scholars, and undergraduate and graduate students. The pilot data were employed to estimate the completion time, verify missingness, and assess internal consistency. Before distributing the final online survey, we revised items A, B, and C in accordance with the results of the attention-check, item-total corrections, and expert feedback.

The final instrument for the online survey was created using the Google Form tool, and then the survey was sent to BNPL consumers through email, WhatsApp, and Facebook. To find

Table 2: Measurement scales

Dimension	Item	Source	Scale
Perceived usefulness - PU	BNPL makes my shopping faster BNPL improves my purchase BNPL makes life easier and peaceful BNPL helps to manage my payments BNPL is useful BNPL improves my spending habits	Davis (1989; 1993); Fortes and Rita (2016)	Likert 1-5
2. Perceived ease of use - PEU	BNPL payment to easy to use BNPL steps are quite simple I learn BNPL mode of payment quickly Using BNPL needs no any help BNPL is user-friendly BNPL use is effortless	Davis (1989); Fortes and Rita (2016)	Likert 1-5
3. Gamification - GM	BNPL feels fun to use I enjoy BNPL offers I like BNPL badges BNPL makes shopping fun-loving BNPL gives reward feeling Using BNPL feels attractive	Baptista and Oliveira (2017); Sigala (2015)	Likert 1-5
4. Perceived value - PV	BNPL saves my money BNPL is cost-effective BNPL saves my time BNPL offers real benefit BNPL is worth using BNPL gives good value	Xie et al. (2021)	Likert 1-5
5. Attitude - ATT	I like BNPL BNPL is a good idea I feel happy using BNPL BNPL sense right BNPL gives me support I enjoy using BNPL	Belanche et al. (2012)	Likert 1-5
6. Behavioral intention - BI	I will use BNPL often I plan to use BNPL I will keep using BNPL I will suggest BNPL use I will prefer BNPL next time I will use BNPL again	Venkatesh et al. (2012); Xu et al. (2011)	Likert 1-5
7. Actual use - AU	I use BNPL often I use BNPL monthly I pay my bills using BNPL I buy items using BNPL BNPL is part of my shopping I rely on BNPL service	Martins et al. (2014)	Likert 1-5

BNPL service consumers, the study used a purposive sampling approach, with snowball sampling to follow (Parker et al., 2019). Kirchherr and Charles (2018) proposed using snowball sampling together with purposive sampling to collect data when jumping into a known sampling frame is difficult. The research was conducted in the West and Central zones of Chennai, with university students who were studying Arts and Humanities, Commerce, management, medical, and technology courses. The Google Form questionnaire link was requested to be sent to each of their family members and their acquaintances who indicated usage of BNPL services. The data were collected via an online survey between September and November 2025. Because BNPL would only offer its service products through the online purchasing platforms, an online survey was chosen. There were 310 consumer responses completed, with post-screening findings 30 were invalidly coded, with 280 valid responses left to analyze, resulting in a strong response rate. Accordingly, we determined that it was best to utilize an online survey. Also, universities had the potential to recruit participants from differing demographics and geographical locations due to their students and doctoral researchers, and faculty, who come from various places in Chennai. The introductory letter described BNPL services, as well as the intent of the research study, and began the survey questionnaire. To ensure the responses were valid and coming from existing consumers of BNPL services, a screening question was directly asked prior to the primary questionnaire's start: "Have you ever used BNPL services?"

3.4. Data Screening and Normality

Before conducting statistical analyses, a thorough examination of the dataset for accuracy, completeness, and multivariate fit was conducted. Cases with missing values and pattern responses were removed from the dataset. The final valid sample available for analysis included 280 cases. Descriptive statistics were employed to explore key demographic and measurement variables from the datasets. All constructs were assessed for normality using skewness and kurtosis values for dataset normality assessments. Based on the criteria proposed by Hair et al. (2019), the data is considered to be approximately normally distributed if skewness and kurtosis are in a reasonable and prescribed range of ±2.58. The skewness values ranged from –0.035 to +0.440 with kurtosis between –1.650 and –0.156, which fell into the range. Hence, normality was approximated for the present sample, with roundness indicated, and subsequently, the sample is acceptable for PLS-SEM analysis.

3.5. Common-Method Bias (CMB)

As the data was gathered by self-report via questionnaire, we assessed for possible CMB utilizing Harman's single-factor test (Podsakoff et al., 2013). We carried out exploratory factor analysis (EFA) on all measure items with no rotation (to understand if a single factor would account for the majority of the variance across the variables). The results from the EFA indicated the first factor accounted for <50% of the total variance, and thus we can conclude that CMB does not pose a significant threat in the current study; Hence, in what follows, the relationships between constructs do not require exaggeration as a result of common method variance.

3.6. Analytical Approaches

PLS-SEM, a variance-based method that evaluates the suggested theoretical model over two stages, was employed in this study (Anderson and Gerbing, 1988). The analysis was carried out using SPSS software for the descriptive statistical analysis and Smart PLS4 analysis software (Ringle et al., 2015). When analyzing questionnaire data to predict or identify important components of a construct, PLS is a reliable method. PLS is also ideal for complex data, small samples, and multicollinearity present in the data (Khan et al., 2022). When designing research as exploratory research and a complex theoretical framework is investigated, in terms of linkages among constructs, PLS-SEM is the best option (Becker et al., 2023). When explanatory research relies on a complex theoretical model with many factors and a small sample size, PLS-SEM is still regarded as the best option among multivariate statistical methods. Finally, in exploratory research, a theoretical model is more exploratory in nature and doesn't have a significant amount of establishment; PLS-SEM is again well-suited toward providing some statistical power. For these reasons, it is a recommended exploratory modelling method when the theoretical model is less established (Hair et al., 2017). The decision to use PLS-SEM rather than covariance-based SEM (CB-SEM) was justified for several reasons. First, this study was predictive in nature, focused on looking at the determinants associated with adopting BNPL (not testing an established theory). Additionally, PLS-SEM handles non-normal data distributions better than CB-SEM and, similarly, is best utilized when the data have moderate deviations from normality—as shown by skewness and kurtosis. Finally, with a moderate sample size (n = 280) and modeling multiple latent variables and interrelationships, PLS-SEM was utilized in the context of the study because it has better statistical power and the ability to accurately model complex models on small-to-medium-sized samples of data (Hair et al., 2017; Khan et al., 2022).

4. DATA ANALYSIS

4.1. Descriptive Statistics

To gain insights into the respondents' demographic characteristics, their responses were analyzed for five important characteristics (gender, age, educational qualification, use of BNPL service, frequency of use of BNPL service, type of housing arrangement, and length of use). Normality was examined with the use of skewness/kurtosis statistics produced by SPSS version 28. Skewness values ranged from −0.035 to +0.440, and kurtosis values ranged from −1.650 to −0.156. Since all values fall within the acceptable range of ± for skewness and ± for Kurtosis (Kline, 2023; Hair et al., 2019), the data can be observed as approximately normally distributed. Accordingly, the dataset is suitable for further multivariate analysis. Results from these attributes are illustrated in Table 3.

4.2. Measurement Model

4.2.1. Indicator multicollinearity

The variance inflation factor (VIF) is used to examine the multicollinearity or collinearity of the indicators (Kim, 2019). Table 4 reveals that all inner VIF values are under 5. Thus, there is no evidence of multicollinearity in the model.

4.2.2. Item and Construct reliability

In order to determine the reliability of the measurement model, the study examined the construct and reliability. First and foremost, it is expected that the coupling of each item to its corresponding latent construct should be equal to or exceed 0.7 to determine the reliability of items used to measure a particular construct (Hair et al., 2019). As the loading of all items exceeds this threshold limit, we can thus identify that our model passes this assessment. Secondly, we tested for construct reliability by measuring Composite Reliability (CR) and Cronbach's Alpha (CA) values. The findings (Table 5) indicate that the CA and CR values for all of the constructs exceed the 0.7 threshold, which indicates moderate internal consistency.

4.2.3. Convergent validity

In this study, we establish the convergent validity of the constructs using average variance extracted (AVE), which is a measure of the degree of correspondence between items that constitute a variable (Henseler et al., 2009). A construct has an AVE that is considered acceptable when it exceeds the value of 0.5. Our measurement model produced AVE values for each construct between 0.602 and 0.77 (Table 5), which is an acceptable value as it exceeded the threshold limit of 0.5. The results suggest good convergence of the constructs of the model.

4.2.4. Discriminant validity

Once the convergent validity of our model was established, the next step involved analyzing the discriminant validity, a new criterion suggested by Fornell and Larcker (1981). To demonstrate discriminant validity, the square root of the AVE value for each construct should be higher than its correlation with the other constructs. The present study shows that this is the case; see Table 6, below. This indicates that the constructs of our model are not highly correlated.

Global goodness-of-fit indices provided by SmartPLS 4 were used to assess the model fit: SRMR, NFI, and RMS_θ present the closeness of the expected covariance matrix of the structural model to the observed covariance matrix.

Henseler et al. (2014) and Hair et al. (2019) report that an SRMR value of <0.08 indicates that a model fits well, whereas NFI values that approach 1.0 indicate a robust comparative fit of the proposed model and the saturated model. For the RMS_θ index, values of <0.12 should reasonably indicate the quality of the model and low residual variance of reflective constructs.

Table 3: Respondent's profile

Demographic variables	n	Minimum	Maximum	Mean	Std. deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Gender	280	1.00	3.00	1.5857	0.56778	0.310	0.146	−0.808	0.290
Age	280	1.00	4.00	2.2143	0.84908	0.318	0.146	−0.470	0.290
Educational qualification	280	1.00	4.00	2.3429	0.66420	0.075	0.146	−0.155	0.290
Using the BNPL service	280	1.00	5.00	2.7964	1.23769	0.450	0.146	−0.996	0.290
Frequency of using BNPL	280	1.00	5.00	2.6714	1.31134	0.338	0.146	−1.050	0.290
Living house	280	1.00	3.00	2.0179	0.86117	−0.034	0.146	−1.654	0.290
Valid N (listwise)	280								

Source: Author's own work

Table 4: VIF values

	ATT	AU	BI	GM	PE	PU	PV
ATT			1.799				
AU							
BI		1					
GM	1.662		1.799				1
PE	1.499					1	
PU	1.584		1.819				
PV			1.935				

Source: Author's own work

Table 5: Reliability and validity

Constructs	Item	Item loadings	CA	CR	AVE
Attitude	ATT1	0.936	0.971	0.971	0.873
	ATT2	0.931			
	ATT3	0.932			
	ATT4	0.932			
	ATT5	0.931			
	ATT6	0.946			
Actual usage	AU1	0.929	0.949	0.95	0.868
	AU2	0.937			
	AU3	0.929			
	AU4	0.932			
Behavioral intention	BI1	0.935	0.969	0.97	0.866
	BI2	0.931			
	BI3	0.931			
	BI4	0.922			
	BI5	0.931			
	BI6	0.934			
Gamification	GM1	0.941	0.967	0.967	0.857
	GM2	0.933			
	GM3	0.918			
	GM4	0.934			
	GM5	0.915			
	GM6	0.915			
Perceived ease of use	PE1	0.915	0.964	0.965	0.847
	PE2	0.92			
	PE3	0.905			
	PE4	0.933			
	PE5	0.924			
	PE6	0.925			
Perceived usefulness	PU1	0.929	0.966	0.966	0.854
	PU2	0.925			
	PU3	0.921			
	PU4	0.927			
	PU5	0.911			
	PU6	0.931			
Perceived value	PV1	0.914	0.968	0.969	0.862
	PV2	0.933			
	PV3	0.939			
	PV4	0.932			
	PV5	0.933			
	PV6	0.921			

Source: Author's own work

The model in this study yielded an SRMR value of 0.056, an NFI value of 0.912, and an RMS_θ value of 0.098, which are all within acceptable thresholds. Therefore, it is confirmed that the extended TAM model, which includes identified GM constructs and PV, fits appropriately to the data, which indicates that the measurement and structural model specifications are appropriate for future research.

4.3. Structural Model

Table 6: Fornell-Larcker criteria

Constructs	ATT	AU	BI	GM	PE	PU	PV
ATT	0.935						
AU	0.517	0.932					
BI	0.532	0.537	0.931				
GM	0.552	0.56	0.507	0.926			
PE	0.566	0.584	0.521	0.526	0.92		
PU	0.552	0.581	0.575	0.562	0.491	0.924	
PV	0.586	0.534	0.544	0.577	0.536	0.586	0.929

ATT: Attitude, AU: Actual usage, BI: Behavioral intention, GM: Gamification, PEU: Perceived ease of use, PU: Perceived usefulness, PV: Perceived value. Source: Author's own work

Table 7: Hypotheses testing results

Hypotheses	Relation	β	STDEV	T-values	P-values
H_1	ATT -> BI	0.192	0.06	3.191	0.001
H_2	PU -> BI	0.283	0.058	4.927	0.000
H_3	PU -> ATT	0.264	0.056	4.711	0.000
H_4	PE -> PU	0.491	0.044	11.201	0.000
H_5	PEU -> ATT	0.309	0.06	5.177	0.000
H_6	PV -> BI	0.188	0.063	2.98	0.003
H_7	GM -> PV	0.577	0.042	13.602	0.000
H_8	GM -> ATT	0.241	0.056	4.284	0.000
H_9	GM -> BI	0.134	0.064	2.073	0.038
H_{10}	BI -> AU	0.537	0.043	12.554	0.000

Source: Author's own work

Table 8: Interpretation of endogenous construct R^2 and Q^2 values

Endogenous construct	R^2-value	Interpretation (R^2)	Q^2-value	Interpretation (Q^2)
ATT	0.454	Moderate	0.394	Large predictive relevance
AU	0.289	Weak	0.253	Medium predictive relevance
BI	0.435	Moderate	0.318	
PU	0.242	Weak	0.236	Medium predictive relevance
PV	0.333	Moderate	0.329	Medium predictive relevance

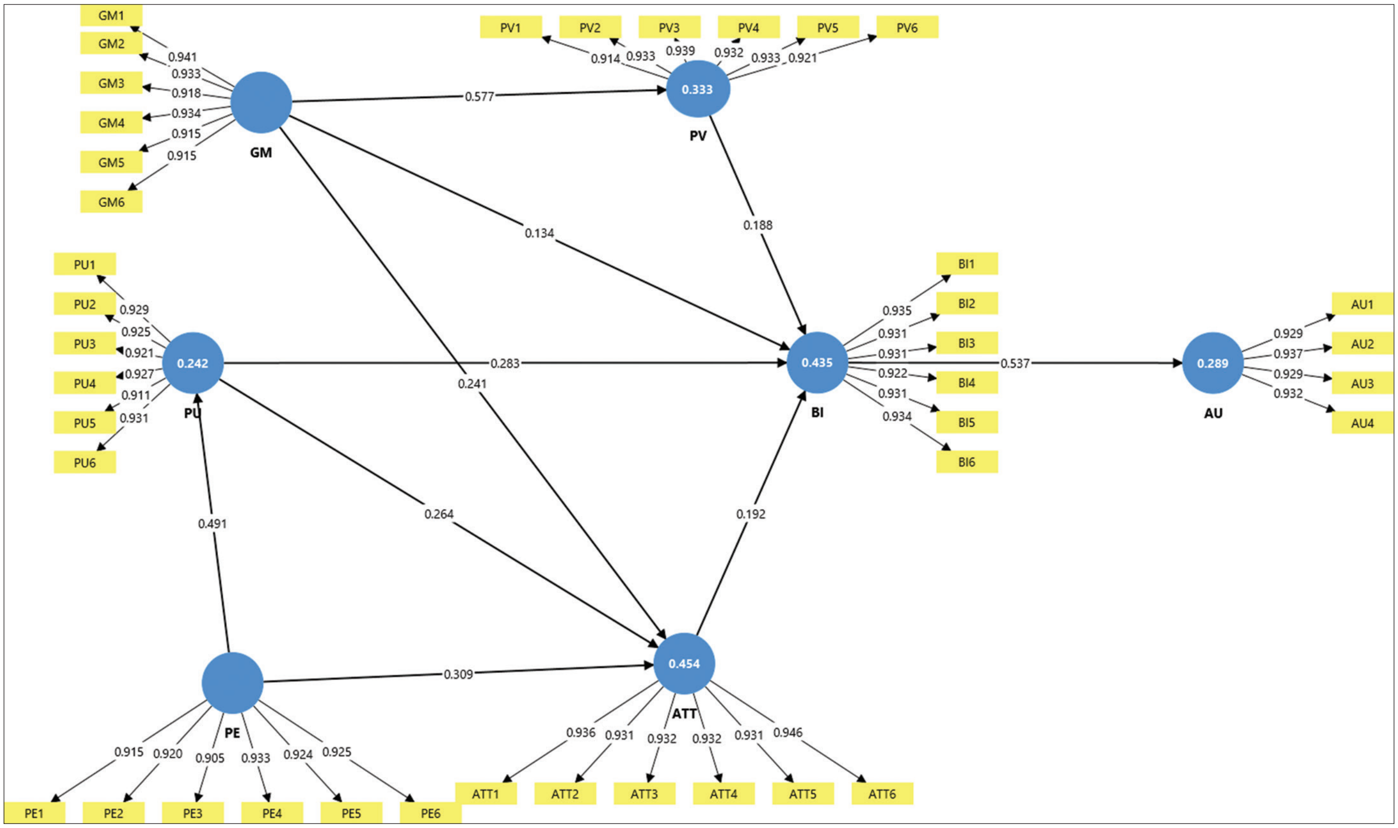
Source: Author's own work

To examine the hypotheses formulated from the research model, path analysis was applied with a bootstrapping approach to determine the t-values based on 5000 samples. The path coefficients, t-statistics, and significance levels of the constructs are displayed in Table 7 (along with the PLS estimates). The results related to the path model are also illustrated in Figure 3.

SEM results have demonstrated support for all the proposed hypotheses, as demonstrated by the significant $P < 0.05$. This implies that the data support the relationships put forth in the hypotheses.

According to Hair et al. (2021), the coefficient of determination (R^2) is a valuable indicator of a PLS-SEM path model's explanatory power. The PLS-SEM path model as presented above shows that PV, PU, ATT, and GM together predict 43.5% of the variance in users' BI to use BNPL (Table 8 shows the results). The PLS estimates also show that GM predicts 33% of the variance with respect to PV. The model predicts 24.2% of the variance in PU,

Figure 3: Structural model



which is predicted by PEU. ATT has a variance of 45.4% which is explained by GM, PU, and PEU. Actual use is explained by a variance of 28.9%, with BI serving as a key determinant. Each Q^2 value is reviewed to determine the predictive accuracy of the PLS-SEM path model. Q^2 values exceeding 0 indicate predictive ability (Hair et al., 2019), and according to the researchers, it amounts to a small (0.23), medium (0.39), and large degree of prediction. After revealing results, all Q^2 values in fact exceed 0, demonstrating substantial explanatory power of the model.

5. RESULTS AND DISCUSSION

The results showed that PEU plays an important role in both PU and ATT towards BNPL. When users think that the BNPL application is easy or simple to use, they perceive it as more useful and attitudinally correspondingly. This finding aligns with previous TAM-based research (Davis, 1989; Venkatesh et al., 2012) and is now also supported by new research about digital payment approaches to usability (Hidayat et al., 2024; Putri et al., 2023), which has shown that usability precedes use. PU also positively influences ATT and intention to act. This finding complements the literature on digital finance (Yadav and Shanmugam, 2024; Vuković and Kundid, 2019), which showed that if users feel BNPL enhances their purchasing ability or gives them improved flexibility in financial management, they would be more likely to adopt BNPL and continue with it. GM made an important contribution to this model and further helps inform our understanding of BNPL adoption. Game-like elements, such as rewards, challenges, and monitoring, act as a mechanism for engaging users for fun and enjoyment and can result in a positive user experience and more motivation for use of BNPL. This supports the research of Baptista and Oliveira (2017) and Ciunova-Shuleska et al. (2022), which found that gamified systems could lead to greater user satisfaction and users continuing to use dedicated fintech platforms. The construct of perceived value PV was also a strong predictor of bi. Therefore, if consumers judge that the perceived value or benefits outweigh the costs of use, they are more likely to accept BNPL, including convenience, flexibility, and savings. This aligns with the literature (Lin et al., 2020; Hegawan et al., 2023), which identifies PV as a significant predictor of technology acceptance and consumer satisfaction in digital financial services. The findings indicate that ATT towards BNPL is a strong predictor of Behavioural Intent, and that intent predicts AU. The results also support classic behavioural theories (Ajzen and Fishbein, 1977; Ajzen, 1991), as well as behavioural research in the fintech context (Safari et al., 2022; Elhajjar and Ouaida, 2019), which show that a positive ATT leads to continued future use.

5.1. Theoretical Implications

5.1.1. Core TAM relationships

The newly developed model contains aspects of the TAM with additional features such as PV and GM. The combined model, as evidenced, accounted for 43.5% of the variance of the BI of BNPL users. The results confirm that PEU influences PU and ATT positively towards BNPL. This suggests that if the BNPL interface is easy to use and navigate, students are more likely to develop positive ATT towards using BNPL. Specifically, PU significantly affects both construct ATT and BI to use BNPL. These results align with the previous digital payment studies (Safari et al., 2022); (Elhajjar and Ouaida 2019); (Firmansyah et al., 2022); (Vuković and Kundid, 2019). Furthermore, ATT toward BNPL emerged as a strong predictor of BI (β = 0.192, P = 0.001), while BI strongly predicted the AU construct (β = 0.537, P = 0.000). The findings strengthen the evidence that positive psychological ATT among students toward BNPL is directly correlated with increased adoption of BNPL and AU behavior among university students. The more positive students perceive BNPL, that will be stronger their intention to use BNPL.

5.1.2. Role of gamification

Both PV (β = 0.577, P = 0.000) and ATT (β = 0.241, P = 0.000) benefit statistically from GM. This suggests that incorporating game-like elements into BNPL platforms improves user satisfaction and engagement. PV is positively impacted by gamification. This demonstrates how GM raises BNPL users' awareness of value; they experience the advantages when BNPL offers services by implementing game-like features, like reward points, challenges, and progress tracking create emotional involvement, thereby increasing users' perceived worth of the platform experience. Many studies on GM across other disciplines support this as well (Hsu and Chen, 2018); (Hsu et al., 2017); (Yang and Chen, 2017). This indicates that if the BNPL applies game design elements that increase positive ATT to the BNPL service, this has also been captured in previous research (Hamari and Koivisto, 2015; D. Wong et al., 2022). While GM has a positive and statistically significant (β = 0.134, P = 0.038), this indicates that gamified features play an important role in students' motivation to utilize BNPL payment services. Stated differently, BNPL providers embedded interactive elements, such as cash-back challenges, streaks for spending, and milestones for rewards, so users will be encouraged to utilize these services. The elements of interactivity motivate user engagement, create opportunities for engagement to develop positively, elicit excitement around transactions, and encourage users to ultimately strengthen BI. Several previous studies have similar findings as this study (Baptista and Oliveira, 2017); (Rodrigues et al., 2017).

5.1.3. Role of perceived value

Among the external constructs, BI was significantly affected by PV (β = 0.188, P = 0.003). This is consistent with previous research suggesting that the perceived trade-off between benefits and costs is a significant motivating factor in the adoption of technology (Zeithaml, 1988). Students valued the BNPL deferred payments and other benefits, such as zero interest, cash back, and flexibility, in the BNPL context. If students judge BNPL to be more valuable, both economically and experientially, they are inclined to choose BNPL for payment.

6. CONCLUSION AND PRACTICAL IMPLICATIONS

Findings from this research provide useful implications for BNPL providers, fintech marketers, educators, and policymakers who are interested in discouraging shameful digital credit practices.

1. Interactive interface design: The considerable indirect influence of GM on BI through ATT and PV highlights the fact that any BNPL platform should include interactive, reward-based, and progress-tracking features to improve engagement. Such strategies must be designed in a way that promotes responsible financial behavior, rather than impulsive spending
2. Facilitating PV through incentives and transparency: BNPL providers should support students' monetary value (cash backs, discounts) but also non-monetary value (transparency, usability, flexibility) due to the strong relationship between PV and intention. As student consumers value trust and satisfaction, they maximise the value they perceive of BNPL, due to better communication on repayments and charges
3. Simple UX: PEU is so important, requiring a BNPL service that is easy and seamless to use. Immediate approval, easy registration, and a single click for payment can all heighten comfort while using the BNPL service
4. Students are being targeted with educational and social campaigns: The behavioral intentions of university students will be influenced by both attitudinal and experiential. For this reason, fintech marketers should pair digital advertising with financial literacy programs, allowing students to understand both the benefits and limitations of using the BNPL services
5. AI-enhanced personalization: Personalization through design into offers or repayment options can increase PV and utility from AI recommendation systems. Personalizing offers contributes to informed and responsible spending while increasing intention to utilize BNPL service.

6.1. Limitations

It is important to highlight the limitations of the study. The sample and time frame were narrow in scope, indicating that the findings of the analysis are contextual within the time frame and are not generalizable to different time frames. Additionally, the researcher limited the examination of BNPL to the study of BNPL consumers. This level of focus limits the usefulness of the findings to other industries or consumers. The findings of the study may not adequately represent the unique characteristics and variations of other user types among those in the sample. The study was also limited in scope in that game elements may well be engaging to a younger audience, such as university students, while they would likely be of no interest to middle-aged or older users. More meaningful and specific insights into a range of identities present in the differing groups would have come from more nuanced forms of analysis among users. A fuller understanding of BNPL purchasing and use would come from future research that considers and unpacks these limitations while considering a wider range of consumer groups, time frames, and variables.

6.2. Future Research

The existing model could be broadened to include the wider psychological and financial variables surrounding BNPL usage by adding additional constructs that include, but are not limited to, perceived risk, trust, financial self-efficacy, self-control, or financial anxiety. The study utilized a cross-sectional research design, yet longitudinal approaches could be utilized in future studies to measure and capture change in actual and behavioral intention of BNPL over time. Experiment studies could also be used to test the causation of gamified features or reward systems to proactively obtain an impulsive purchasing behavior and measure repayment borrowing. If the model is replicated across different cultures, income brackets, or ages, there might be different avenues of BNPL acceptance that emerge. Insight into the ways in which users' perceptions of gamified BNPL platforms are influenced by cultural values, regulatory environments, and financial literacy could be gained through comparative research across developed and developing economies. Future research could utilize moderated-mediation models to investigate the interaction between constructs such as Social Media Intensity, Peer Influence, or Financial Literacy and PV and ATT in the prediction of BNPL intention. This would facilitate the theoretical infusion of perspectives from behavioral economics, S-O-R, and TAM. Future research may investigate ethical GM strategies and responsible digital finance frameworks in response to increasing concerns regarding impulsive spending and over-borrowing. Researchers can examine the impact of transparent reward systems and educational interventions on the sustainable financial behavior of young people.

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