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The Determinants Impacting the Willingness to Use Fintech Payment Systems: The Case of Buy Now and Pay Later (BNPL)

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Abstract: BNPL (Buy Now, Pay Later) services have swiftly gained prominence globally as a notable fintech payment innovation. In Saudi Arabia, a supportive fintech ecosystem and a tech-savvy young population have driven rapid BNPL uptake, underscoring the importance of examining factors influencing its adoption. This study adopts the PPM theory and employs a quantitative survey involving 158 Saudi BNPL users to identify key determinants of switching intention. The findings revealed that personal innovativeness, financial risk tolerance, privacy risk tolerance, and perceived value all demonstrated noteworthy positive impact on users' intention to switch to BNPL solutions. In contrast, social influence did not show a substantial effect on the willingness to adopt BNPL solutions. These findings highlight the primacy of individual traits and perceived value over social factors, reinforcing the PPM framework's relevance for fintech adoption in emerging markets. The findings provide valuable guidance for fintech companies and regulators to enhance perceived value and address risk concerns to foster BNPL adoption.

Keywords: BNPL; fintech; PPM model; switching intention; emerging markets

1. Introduction

The emergence of financial technology has significantly transformed consumer behavior, reshaping how individuals engage with digital transactions, credit, and payment systems. Among the most prominent of these innovations exists the Buy Now, Pay Later (BNPL) solutions, offering consumers the ability to postpone payments without incurring interest, often bypassing traditional credit mechanisms [1]. This short-term credit option, usually facilitated through mobile applications at the point of sale, has surged in popularity across global markets, particularly in regions experiencing rapid digital transformation [2]. The BNPL solutions permit users to request for and obtain consent for installment-based payments during the purchase process through BNPL applications [3]. Upon receiving approval, the user is able to acquire merchandise and services and repay the amount via a sequence of payments. In 2023, the global BNPL market was valued at USD 316 billion, and it is forecasted to grow to over USD 687 billion by 2028. This significant increase underscores the widespread adoption of BNPL services and their expected continued growth and sustainability in the coming years [2].

Saudi Arabia, situated at the nexus of digital innovation and socio-economic reform, offers a unique context for examining BNPL adoption. As part of its Vision 2030 strategy, the Kingdom has positioned the fintech as a central pillar for economic diversification and financial inclusion [4]. According to a recent report by [5], Saudi Arabia is experiencing significant growth in the BNPL sector, largely attributed to the government's support for the development and adoption of fintech solutions. With over one-third of its population under the age of 30, Saudi Arabia represents an ideal setting to assess the behavioral determinants influencing the adoption of emerging payment systems, particularly among younger, tech-savvy consumers [6]. Despite strong government support and increasing fintech infrastructure, BNPL adoption remains heterogeneous, with disparities observed across demographic lines and digital literacy levels [7].

From an academic standpoint, most prior studies on BNPL adoption have been framed within classical technology acceptance models, such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), or the Innovation Diffusion Theory (IDT) [8, 9]. While these models have successfully identified key enablers for instance ease of use and perceived usefulness, they frequently overlook the nuanced interplay between enabling factors (push), attractive attributes (pull), and restraining conditions (mooring) that shape real-world switching behavior [10]. Moreover, few studies have adequately accounted for inhibiting forces such as privacy risks, financial anxiety, or innovation resistance, which may co-exist with adoption drivers [11].

To address these limitations, this study applies the Push–Pull–Mooring (PPM) framework, initially created to understand migration patterns, but increasingly employed in digital platform research [12]. The PPM framework categorizes the determinants of switching intention into three dimensions: Push factors, which reflect dissatisfaction with current solutions (e.g., low perceived value or social disapproval); Pull factors, which attract users to a new system (e.g., convenience, low financial risk); and Mooring factors, which either facilitate or inhibit switching behavior depending on individual traits (e.g., personal innovativeness) [13, 14].

Given the scarcity of context-specific research on BNPL adoption using the PPM framework in the Saudi context, this study aims to fill this gap by exploring the subsequent research questions:

1. RQ1: To what degree do push variables affect users' switching intention to use fintech payment systems?
2. RQ2: To what degree do pull variables affect users' switching intention to use fintech payment systems?
3. RQ3: To what degree do mooring variables affect users' switching intention to use BNPL services?

To explore these questions, we adopt a quantitative, cross-sectional survey approach targeting individual users in Saudi Arabia (both Saudi and non-Saudi residents), with all variables grounded in recent empirical literature. The goal of this research is to offer both conceptual and actionable insights by expanding the application of the PPM framework and offering insights for policymakers and digital service designers seeking to enhance BNPL adoption.

2. Literature Review

Adopting the BNPL fintech solutions has sparked considerable scholarly interest in understanding the psychological, social, and contextual factors influencing switching behavior. Although conventional technology acceptance models, for instance TAM and UTAUT have helped identify key drivers of fintech use [7,8], they often overlook the multifaceted motivations and frictions that shape consumers' intentions to switch from conventional payment systems to newer alternatives. The Push–Pull–Mooring (PPM) model offers a more holistic framework to study these dynamics by incorporating motivating forces (push), attracting elements (pull), and restraining or enabling individual characteristics (mooring) [12].

2.1 Push Factors

2.1.1 Perceived Value (PV)

Perceived value is one of the strongest push factors influencing users' dissatisfaction with existing financial tools, motivating them to seek superior alternatives. Within the framework of BNPL, perceived value pertains to how strongly users feel that the BNPL service provides a better or more efficient payment experience compared to existing alternatives. BNPL encompasses time-saving convenience, ease of transaction, and cost-effectiveness compared to traditional credit systems. [4] discovered that within the demographic of Saudi Gen Z users, performance expectancy—how useful and efficient the BNPL app was—significantly predicted continued use. The perceived affordability and flexibility of BNPL payments made them a viable substitute for conventional payment modes. Similarly, [10] showed that the perceived simplicity and immediacy of BNPL apps in Malaysia made users feel they were receiving more value compared to complex credit instruments. Furthermore, [15] suggested that people's willingness to adopt internet-based wealth management podiums is closely tied to their behavior regarding their patterns of engaging with financial services. Thus, when users perceive BNPL as offering convenience, cost savings, or transactional ease, they are more inclined to consider switching.

Hypothesis 1: *Perceived value (PV) significantly impacts the intention to switch to BNPL solutions (iBNPL) in a positive manner.*

2.1.2 Social Influence (SI)

Social influence reflects the level at which users' decisions are shaped by the opinions, behaviors, or endorsements of others. The study conducted by [15] mentioned that a variety of studies show that social influence has a positive impact on the actions and decisions of users. In addition, [16] highlighted that social influence acts as an intermediary factor, significantly affecting consumers' intentions to use technological innovations. In addition, [9] demonstrated that peer and social media influence played a substantial role in BNPL adoption among Malaysian youth, who tended to follow digital payment trends endorsed by influencers or close social circles. A study by [7] confirmed similar findings in Saudi Arabia, where family and peer perceptions were key determinants in technology adoption under the UTAUT2 framework. This reinforces the idea that perceived social approval can push users away from traditional payment methods toward BNPL systems, especially in collectivist societies.

Hypothesis 2: *Social influence (SI) significantly impacts the intention to switch to BNPL solutions (iBNPL) in a positive manner.*

2.2 Pull Factors

2.2.1 Financial Risk Tolerance (FRT)

Financial risk tolerance (FRT) refers to the degree of comfort users have with the potential for financial loss or market fluctuations. A study by [17] indicated that risk tolerance significantly influences performance outcomes and decision-making intentions. While traditional models focus on perceived risk as a deterrent, [14] show that higher FRT can serve as a pull factor—encouraging individuals to try BNPL services because they feel confident in managing repayment [18] discovered that individual with higher risk tolerance is inclined to accept financial technology, as he believes able to handle the risks associated with using this type of technology. Soong et al. (2024) [1] discovered that a significant number of adults view BNPL as a less risky option compared to credit cards, primarily due to transparent installment plans and lack of interest, which improves their confidence in using the service. Additionally, [11] reports that financial literacy and trust mitigate perceived risks, transforming FRT into a driver of adoption.

Hypothesis 3: *Financial risk tolerance (FRT) significantly impacts the intention to switch to BNPL solutions (iBNPL) in a positive manner.*

2.2.2 Privacy Risk Tolerance (PRT)

Privacy concerns are a notable barrier to digital adoption, yet tolerance of privacy risk may pull users toward new systems. In the fintech domain, users often trade privacy for convenience. A study by [19] found that although consumers were aware of potential data misuse in fintech platforms, they continued to use BNPL apps due to their ease and speed. In addition, [14] confirmed that privacy risk did not significantly deter BNPL adoption when convenience and social approval were high. In addition, [20] provided empirical evidence that users emphasize privacy protection when considering the usage of digital payment. Furthermore, [21] further affirms that privacy emerges as one of the most significant determinants of Robo advisor adoption. These findings suggest that individuals with high privacy risk tolerance may be more inclined to adopt BNPL despite uncertainties.

Hypothesis 4: *Privacy risk tolerance (PRT) significantly impacts the intention to switch to BNPL solutions (iBNPL) in a positive manner.*

2.3 Mooring Factors

2.3.1 Personal Innovativeness (PI)

Personal innovativeness—defined as the willingness to try out new technologies—acts as a critical mooring factor. Users with higher innovativeness are more likely to overcome switching inertia and explore new financial tools. A study by [22] identified personal innovativeness as a major predictor of fintech experimentation. In addition, [23] expanded on this by linking innovativeness to positive perceptions of BNPL flexibility and usefulness. Also, [13] revealed that trust, along with the perceived ease of use, played a facilitating role in the connection between innovativeness and the decision to adopt the technology, suggesting that personal traits help users move past psychological barriers to switching.

Hypothesis 5: *Personal innovativeness (PI) significantly impacts the intention to switch to BNPL solutions (iBNPL) in a positive manner.*

2.4 Switching Intention to iBNPL

Switching intention denotes a person's readiness to move away from their existing systems or services in favor of adopting new alternatives. Several studies have contextualized switching intention in terms of satisfaction, performance expectations, and platform trust. In addition [8], highlighted how psychological rewards such as instant gratification and reduced cognitive load influenced users' decision to continue using BNPL. Also, [12] explicitly applied the PPM framework and found that push factors like dissatisfaction with traditional banking and pull factors like perceived fairness of fintech systems predicted switching intention. In the Saudi context, [4] confirmed that social influence and system quality were key contributors to intention among Gen Z users.

Table 1: Summary of the PPM Literature in Fintech Adoption

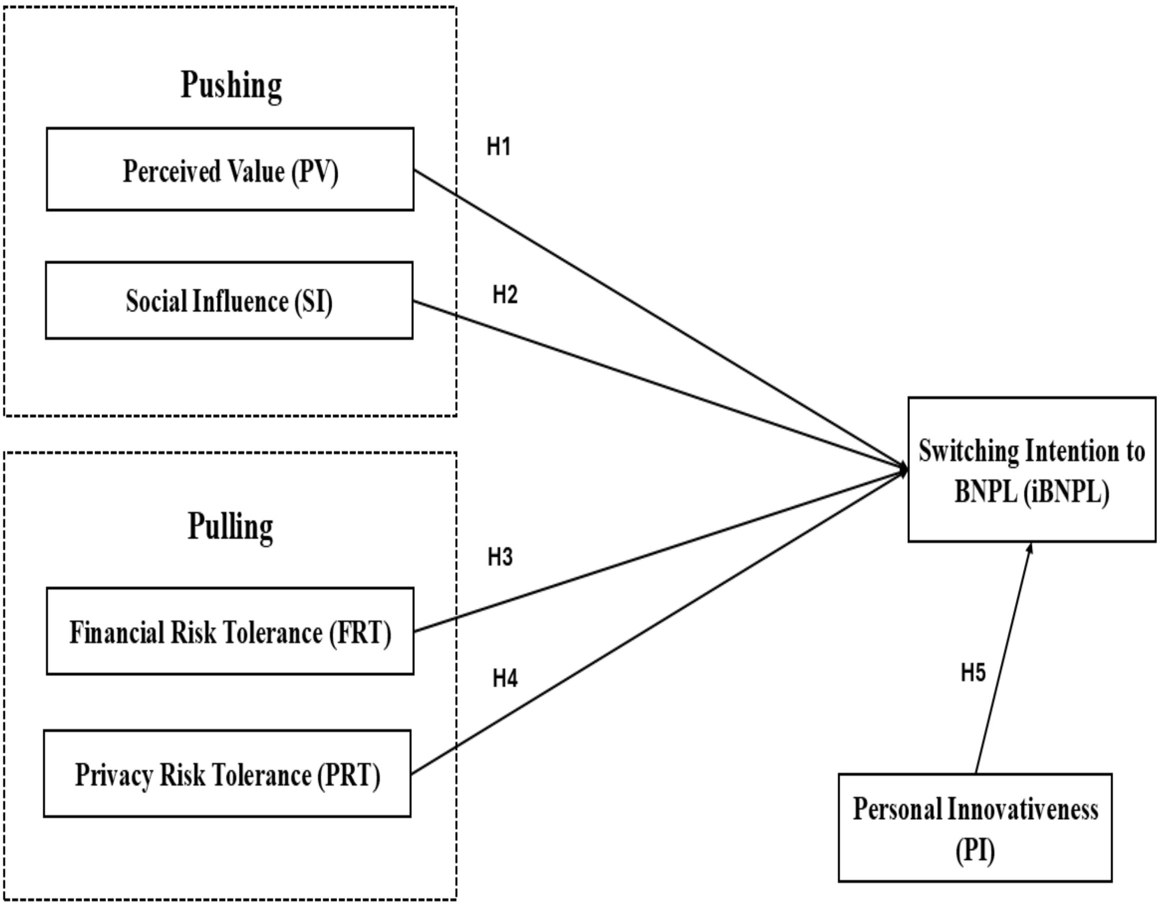
Factor Type	Variable	Key References
Push	Perceived Value	[10], [15]
	Social Influence	[9], [7], [15], [16],
Pull	Financial Risk Tolerance	[1], [14] , [17] [18]
	Privacy Risk Tolerance	[14], [19], [20], [21]
Mooring	Personal Innovativeness	[13], [22], [23]
Outcome	Switching Intention	[8], [12].

3. Methodology

3.1 Research model

This research utilized a quantitative cross-sectional survey approach to investigate the push, pull, and mooring elements that influence the willingness to transition to BNPL solutions within Saudi Arabia. The use of a quantitative methodology is suitable because it enables the statistical analysis of relationships between the hypotheses and offers findings that can be generalized to the broader user population [24]. The target population was individual consumers (both Saudi nationals and expatriate residents) who are familiar with digital payments. The research model (Figure 1) was grounded in the Push–Pull–Mooring framework, incorporating five independent variables – two push factors (perceived value and social influence), two pull factors (financial risk tolerance and privacy risk tolerance), and one mooring factor (personal innovativeness) to estimate the dependent variable representing the intention to transition to BNPL solutions (iBNPL).

Fig. 1: Research Model



3.2 Population and Sampling

The data for this study were gathered by distributing an online questionnaire survey targeting participants within Saudi Arabia. A non-probability convenience sampling approach was used to reach potential BNPL users via social media and email invitations. To encourage participation, respondents were assured of anonymity and that the survey was for academic research purposes only. This approach is thought to have a higher probability of producing a sufficient number of replies that are unique and of preventing respondents from responding more than once. Through the use of Google Forms, the researcher distributed the questionnaire to the participants, and 168 responses were obtained. For the purpose of identifying missing data, biased replies, and outliers, the research used a variety of different metrics. As a result, ten of the respondents were eliminated, leaving 158 respondents to carry out the analysis.

Table 2: Demographics Statistics (N = 158)

Element	Occurrence	Rate of Occurrence (%)
Gender		
Male	109	69
Female	49	31
Age		
Below 20	2	1.3
20 – 30	36	22.7
31 – 40	44	28
41 – 50	49	31
above 50	27	17
Education		
High School	23	14.5
Diploma	15	9.5
Bachelor	77	49
Master	21	13
Doctorate	22	14
Experience		
Less than one year	64	40.5
over one year to three years	58	36.5
over three years to five years	24	15.2
over 5 years	12	7.8

3.3 Research Framework and Measures

The survey tool comprised organized questions, systematically arranged into sections corresponding to each construct within the research framework. All constructs were measured with multiple items adapted from previously validated scales in the fintech and technology adoption literature, then tailored to the BNPL context. The study will utilize a structured, web-based questionnaire composed entirely of closed-ended questions to gather responses. The questions included in the questionnaire will be based on well-established measurement scales from earlier research to ensure that the data collected are both reliable and valid, as illustrated in Table 1.

3.4 Data Analysis Procedure

The gathered data were examined through structural equation modeling employing the PLS-SEM and using the SmartPLS 4 software to conduct the analysis. This method was selected because it is well-suited for predictive research frameworks and demonstrates strong performance even with sample sizes that are small to medium in scale [25]. A two-step analytical strategy was employed. Initially, a measurement model evaluation, specifically confirmatory factor analysis (CFA), was performed to assess the reliability and validity of the constructs within the study. This process included checking internal consistency through metrics such as Cronbach's alpha and composite reliability, evaluating convergent validity by examining the average variance extracted (AVE) and the indicator loadings, as well as verifying the discriminant validity among all latent variables. After confirming that the measurement model met the required standards, the analysis proceeded to evaluate the structural model, which involved testing the proposed hypotheses and the relationships between the constructs

4. Results

4.1 Measurement Model Results

Prior to hypothesis testing, the measurement model was assessed to ensure both the reliability and validity of the constructs. The reliability metrics for each latent construct, including CA, CR, and AVE, based on a CFA with 158 respondents were presented in Table 3. All six constructs (PV, SI, FRT, PRT, PI, and iBNPL) had composite reliabilities covering a range from 0.802 to 0.934, surpassing the suggested benchmark of 0.70, indicating sufficient internal consistency. Similarly, most Cronbach's alpha values exceeded the 0.70 threshold [26], confirming good internal consistency; the only exception was perceived value (α = 0.665), which is slightly below the conventional 0.70 cutoff. However, its composite reliability (0.802) and AVE (0.509) were acceptable, suggesting that the construct still demonstrates sufficient reliability for exploratory purposes. The average variance extracted (AVE) for every variable exceeded the 0.50 criterion, with values ranging between 0.509 and 0.780, demonstrating convergent validity. This means that, on average, each variable accounted for more than 50% of the variance in its related items. Additionally, all item factor loadings were statistically significant and generally surpassed the 0.70 mark within their corresponding variables, providing further evidence of the measures' convergent validity.

Table 3: A CFA Results for Latent Constructs (N = 158)

	CA	N	CR	AVE	R2
PV	0.665	4	0.802	0.509	
SI	0.875	4	0.914	0.727	
FRT	0.845	4	0.897	0.687	
PRT	0.841	4	0.893	0.676	
PI	0.815	4	0.880	0.649	
iBNPL	0.906	4	0.934	0.780	0.679

Discriminant validity was evaluated through the Fornell–Larcker criterion. The relationships between variables, with the diagonal displaying the square root of the AVE for each variable as represented in Table 4. In every case examined, the value representing the square root of the average variance extracted (AVE) for each construct along the diagonal was higher than the degree of its relationship with every other construct included in the model. This confirms that the Fornell–Larcker criterion for establishing discriminant validity was successfully satisfied. For instance, the AVE square root for personal innovativeness (0.805) was higher than its correlations with FRT (0.568), PRT (0.565), PV (0.610), SI (0.568), and iBNPL (0.724). This demonstrates that each construct is strongly related to its own set of indicators than to other constructs within the model, providing evidence that the measured variables are capturing distinct theoretical concepts. Additionally, no problematic cross-loadings were observed: every item exhibited its strongest loading on the construct it was designed to measure, compared to all other constructs, further confirming discriminant validity. These findings provide assurance that the questionnaire is both dependable and accurate for examining the structural associations.

Table 4: Discriminant Validity Outcomes (N = 158)

	FRT	PI	PRT	PV	SI	iBNPL
FRT	0.713					
PI	0.590	0.853				
PRT	0.499	0.565	0.829			
PV	0.574	0.610	0.474	0.822		
SI	0.643	0.568	0.413	0.587	0.805	
iBNPL	0.686	0.724	0.612	0.653	0.585	0.883

4.2 Structural Model and Hypothesis Testing

After confirming the validity of the measurement model, this analysis examined the structural model to investigate the research questions and test the hypotheses. The PLS-SEM analysis yielded an R^2 score of 0.679 pertaining to the switching intention to use BNPL (iBNPL), as shown in Table 3, indicating that about 67.9% of the variance in BNPL switching intention is accounted for by combining the push, pull, and mooring factors in our model. This suggests a substantial explanatory power, meaning the PPM-based model is quite effective in accounting for why consumers consider switching to BNPL services. Table 5 provides a summary of the path coefficients along with their corresponding significance levels for each of the hypothesized relationships tested in the study.

Table 5: The Hypothesis Results (N = 158)

Path	path coefficient (β)	Standard deviation (STDEV)	P values	Significance
FRT -> iBNPL	0.266	0.074	0.000	***
PI -> iBNPL	0.318	0.076	0.000	***
PRT -> iBNPL	0.192	0.070	0.006	**
PV -> iBNPL	0.190	0.064	0.003	**
SI -> iBNPL	0.043	0.071	0.546	Not significant

Out of the five hypothesized paths, four were supported by the data ($p < 0.01$ or better), and one was not significant. Among the push factors, perceived value (PV) demonstrated a positive and statistically significant impact on the intention to switch (β = 0.190, p = 0.003), thereby providing support for hypothesis H1. This result implies that consumers who perceive BNPL as offering superior value – for instance, by providing more convenience, savings, or efficiency than traditional payment methods – are more inclined to switch to using BNPL. In contrast, social influence (SI) did not exert a statistically significant influence on the intention to switch (β = 0.043, p = 0.546). Thus, H2 remained unsupported, which suggests that, within the context of this study, the BNPL adoption, the direct effect of peers' and family's opinions or social media trends is relatively weak when it comes to deciding to use BNPL. Consumers appear to base their decision more on personal evaluations of value and risk rather than on social pressure or approval, a point we revisit in the discussion.

Regarding the pull factors, both showed significant positive influences on BNPL switching intention. Financial risk tolerance (FRT) had a β = 0.266 ($p < 0.001$), indicating a substantial impact and supporting H3. This means individuals who are more comfortable with financial risk (e.g., those who don't fear the possibility of missed payments or incurring debt via BNPL) are significantly more likely to intend to use BNPL. Similarly, privacy risk tolerance (PRT) was a meaningful determinant (β = 0.192, p = 0.006), which provided evidence for H4. Users who exhibit tolerance for potential privacy risks – for instance, being less concerned about sharing personal data with BNPL platforms or trusting the platform's security – are more inclined to switch to BNPL services. These findings align with the expectation that a higher tolerance for both financial and privacy risks lowers the psychological barriers to adopting fintech payment solutionsmdpi.commdpi.com.

Finally, the mooring factor of personal innovativeness (PI) emerged as the strongest predictor of BNPL switching intention in this study. PI had a $\beta = 0.318$ ($p < 0.001$), confirming H5. This denotes that individuals who consider themselves innovative and eager to try new technologies have a significantly higher willingness to adopt BNPL services, even when considering the influence of other variables. In fact, personal innovativeness contributed the largest share of explained variance among all factors, underscoring the critical role of inherent consumer innovativeness in fintech adoption. This result is consistent with prior research suggesting that innovative propensity can overcome mooring effects like habit or inertia, facilitating the switch to new digital financial services [13, 22].

5. Discussion

The findings of this study offer robust empirical evidence supporting the use of the Push–Pull–Mooring (PPM) framework to explain consumers' intentions to switch to BNPL solutions within the Saudi Arabian context. Four of the five hypothesized relationships were found to be statistically significant, offering important insights into the behavioral determinants shaping BNPL adoption.

First, personal innovativeness (PI) stood out as the most influential predictor of the intention to switch to BNPL solutions, echoing previous findings from digital payment literature [13, 22]. This suggests that consumers who perceive themselves as early adopters or experimenters with technology tend to be more willing to embrace BNPL solutions, probably because of their greater receptiveness to fintech innovations and their confidence in managing novel digital systems. This strengthens the idea that mooring factors function not just as passive moderators but also as active facilitators in the adoption of fintech services.

Second, both financial risk tolerance (FRT) and privacy risk tolerance (PRT) were significant pull factors. Consumers who are comfortable with financial exposure and less concerned about data-sharing risks were more likely to consider using BNPL. These results are consistent with recent research emphasizing the critical role of individual risk tolerance in the adoption and use of fintech services [18, 19], and affirm that users evaluate not just utility, but also their personal risk thresholds when adopting digital credit systems.

Third, perceived value (PV) significantly influenced switching intention, supporting past research that positions utility, cost-effectiveness, and convenience as key drivers of fintech use [10]. This result affirms the traditional "performance expectancy" element seen in models such as TAM and UTAUT, while expanding it within a PPM framework. BNPL users perceive a clear value proposition in the ability to defer payments without interest, manage budgets flexibly, and access streamlined mobile experiences.

Conversely, social influence (SI) did not significantly predict switching intention. This outcome contrasts with earlier research that highlighted the influence of peer norms and social media trends as significant factors driving fintech adoption [7,16]. One possible explanation is that BNPL adoption in Saudi Arabia may still be viewed as a private financial decision rather than a socially visible behavior, unlike mobile wallets or payment platforms that are used in public or shared contexts. Additionally, it may reflect a generational shift wherein young users prioritize autonomy and personal utility over normative social expectations when making financial decisions. Collectively, these results suggest that the decision to adopt BNPL is more individualistic and risk-driven than socially constructed. The findings also demonstrate the robustness of the PPM framework in capturing these nuanced behavioral dynamics beyond the scope of traditional acceptance models.

6. Academic and Practical Contributions

6.1 Academic Contributions

This research offers multiple important contributions to the academic field. It extends the application of the Push–Pull–Mooring (PPM) model from its traditional roots in migration studies and platform switching behavior to the fintech context, specifically BNPL services. By integrating under-explored factors such as financial and privacy risk tolerance within the pull dimension, the study addresses a gap in literature where risk-related personal characteristics are often marginalized. Additionally, it challenges the primacy of social influence emphasized in UTAUT-based models by showing its limited explanatory power in this context, especially among young consumers in a digitally transforming society. Furthermore, the study contributes to the theoretical integration between individual difference theory (e.g., personal innovativeness) and behavioral intention modeling in financial decision-making, reinforcing the view that personality traits can play a decisive role in technology switching behavior.

6.2 Practical Contributions

From a practical perspective, the results provide valuable guidance for BNPL providers, regulatory authorities, and fintech innovators operating in Saudi Arabia and similar emerging markets. First, providers should target innovative users and early adopters with personalized marketing campaigns that emphasize the novelty and flexibility of BNPL features. Second, given the role of risk tolerance, platforms should implement clear disclosures, transparent repayment terms, and privacy assurances to attract users who may be hesitant due to security or financial concerns. Third, enhancing the perceived value of BNPL through loyalty programs, seamless integration at checkout, and interest-free promotions could drive adoption more effectively than relying on peer endorsements or influencer marketing alone. Finally, policymakers could use these insights to refine consumer protection regulations while still enabling experimentation with digital financial tools under Vision 2030's fintech transformation agenda.

7. Directions for Future Studies

Although the current research offers new perspectives, it additionally paves the way for numerous opportunities for further investigation. First, inclusion of new variables, Subsequent research could include additional psychological or contextual factors, including factors like trust, financial literacy, or digital self-efficacy to deepen the explanatory power of the model. Second, a longitudinal design could track how switching intention translates into actual usage over time and how perceptions of risk or value evolve with repeated use. Third, comparative research: cross-cultural or cross-national comparisons could explore how BNPL adoption differs between regions with varying fintech maturity, financial regulation, and digital culture. Finally, further research could also segment consumers by demographics (e.g., age, income, employment) or lifestyle to identify tailored adoption patterns and motivations

8. Limitations

The current research presents several constraints that must be acknowledged. Firstly, the reliance on convenience sampling restricts the extent to which the findings can be generalized. Although the sample included a diverse mix of respondents, it might not provide a comprehensive representation of the diverse demographics and behaviors found within the overall consumer population in Saudi Arabia. Second, the study's cross-sectional design limits the ability to draw definitive conclusions about cause-and-effect relationships. Although the structural model indicates potential cause-and-effect links between variables, establishing causality requires the use of longitudinal or experimental research designs. Additionally, all variables in this study were assessed using self-reported survey data, which could be influenced by measurement bias or the tendency of respondents to answer in a socially favorable manner, despite efforts to mitigate these issues. Lastly, the study focused exclusively on users aware of BNPL services. It did not examine the barriers to awareness or the perspectives of non-users, which could be a critical area for future research, especially in markets where BNPL penetration is still emerging.

9. Conclusions

This study examined the determinants influencing Saudi consumers' willingness to switch to Buy Now, Pay Later (BNPL) solutions by applying the Push–Pull–Mooring (PPM) framework. The results reveal that perceived value, financial risk tolerance, privacy risk tolerance, and particularly personal innovativeness significantly predict switching intention, whereas social influence does not play a statistically significant role These results highlight the critical role of individual assessment and risk tolerance in fintech adoption decisions, rather than reliance on social approval.

By expanding the theoretical use of the Push–Pull–Mooring (PPM) model and providing detailed understanding of the factors driving consumer behavior in adopting BNPL solutions, this research adds valuable knowledge to the literature on digital payment technologies within emerging markets. It also provides practical guidance to stakeholders seeking to foster sustainable and responsible adoption of fintech innovations under Saudi Arabia's Vision 2030 transformation. Continued research is essential to further unpack the evolving dynamics of BNPL use and its long-term implications for financial inclusion, consumer protection, and digital economic growth.

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