

Adoption of Emerging Digital Technologies in Financial Services: A Behavioural Study of Third-Party Payment Aggregators in India

Ramjan Banu.S^{1*}, Dr. R Guhan^{2*}, Dr. K Nigama³, Dr. M Karthik Ram⁴

^{1*}School of Management, SASTRA Deemed University, Thanjavur

^{2*}School of Management, SASTRA Deemed University, Thanjavur

³School of Management, SASTRA Deemed University, Thanjavur

⁴School of Management, SASTRA Deemed University, Thanjavur

*Corresponding Author Email : ²guhan@mba.sastra.edu

¹ramjanbanus1113@gmail.com

Abstract

Digital banking is essentially about using the internet and mobile technology to effectively carry out and manage your banking needs from anywhere without having to be physically present in a bank. After the demonetization and Covid-19 pandemic, digital banking in India entered the new phase with the advent of Unified Payment Interface (UPI). A payment aggregator is basically a middleman that makes online payments simple and seamless. The Indian payment aggregator market handled transactions worth about INR 265 trillion in FY 2023-24, and this figure is expected to almost double, reaching nearly INR 593 trillion by FY 2028-29. This study employed the purposive sampling technique to collect the samples. The primary data were collected through a survey instrument in the form of a questionnaire. Out of the 600 questionnaires distributed, 572 were successfully completed and deemed valid for analysis. Some limitations arose in collecting information from TPPA users, which slightly constrained the data-gathering process. The primary tool for this study was a questionnaire designed using a five-point Likert scale to measure respondents' perceptions and attitudes. To analyse the data, the study applied SPSS, PLS-SEM through SmartPLS4. This approach allows a thorough assessment of both the measurement and structural models which provide more reliable and precise estimates. The results found that effort expectancy, perceived and social influence has a significant influence on behavior intention of adopting Third Party Payment aggregators in India. And the variables like facilitating condition, perceived cost, performance expectancy and perceived trust have less significant impact on behavior intention.

Keywords: PLS-SEM, Risk, Trust, SPSS, TPPA, UPI

INTRODUCTION

Digital banking is essentially about using the internet and mobile technology to effectively carry out and manage your banking needs from anywhere without having to be physically present in a bank. [1]

We have transitioned from using traditional banking methods to digital and online banking over the years, and we are still seeing the transition today.

Digital banking is really taking the bank-dedicated functions all online, including checking your balance, moving your money from one account to another, paying bills, opening new accounts, and even applying for loans. You can do this all the time, and anywhere, using a computer, smartphone, or ATM.

Digital banking offers you constant access to your finances. However, the difference with digital banking is how it integrates automation and web-based banking platforms or apps along with sometimes APIs (Application Programming Interfaces) to allow banks to connect to other services and financial institutions for a more streamlined process or user experience to help you manage everything in one spot.

Digital banking is becoming more prevalent in India and universally, because of its ease and convenience. But, as with anything there are pros and cons.

After the demonetization and Covid-19 pandemic, digital banking in India entered the new phase with the advent of Unified Payment Interface (UPI). It brings together multiple bank accounts into one

mobile app regardless of which participating bank you use. It also makes easy transfer of money, pay merchants, and manage transactions and allows people to send or request money directly from each other, with the flexibility to schedule payments based on their needs and convenience [2]. By using the UPI platform, many payment aggregators also increased and facilitated the payment eco system in India. A payment aggregator is basically a middle

man that makes online payments simple and seamless. It gives businesses a single platform to accept money in different ways whether that's through debit or credit cards, UPI, bank transfers, digital wallets, card less EMIs or even e-mandates. For customers, it means having the freedom to pay with the method they find most convenient and for businesses, it removes the hassle of setting up separate systems for each payment type [3].

The main purpose of payment aggregators is to make the payment easier for end users particularly business entities to accept payments. They simplify the setup process, connect with different payment methods, and ensure smooth transaction processing and quick settlement of funds. In short, they act as a one-stop solution for businesses to manage all their payment needs efficiently. Some of the examples for payment aggregator are Google Pay, PhonePe, Amazon pay, Razor pay etc., [4]

This study focuses on Bridging Trust and Technology of third-party payment aggregators in India. It focuses only on users who use TPPA for their day-to-day financial transactions. The data also shows that payment aggregators play a vital role in handling financial transaction in India.

The Indian payment aggregator market handled transactions worth about INR 265 trillion in FY 2023-24, and this figure is expected to almost double, reaching nearly INR 593 trillion by FY 2028-29 [5]. By the end of 2025, India is expected to witness over 130 billion digital payment transactions [6].

This study concentrated on UTAUT variables like Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, along with Perceived Risk, Perceived Trust, and Perceived Cost. Objectives of this study is to analyse the respondents based on different demographic statuses to understand

their background and segment their usage patterns of TPPA.

It also examine the relationship between study variables and behavioural intention of using TPPA by respondents by assessing factors like ease of use, trust, usefulness, and security. And this study propose certain policy implication measures that can contribute to the growth of TPPA by suggesting improvements in service delivery, digital awareness, and user experience

THEORITICAL FRAMEWORK AND HYPOTHESES

A. *Performance Expectancy*

Performance expectancy is defined as a user believes a new system or technology will actually help them do their work better, faster, or more effectively [7]. Kumar [8] found that people's expectations about how well digital payments will work strongly influence their intention to use them and their shopping behaviour. Another study reveal that performance expectancy significantly influences users' behavioural intentions and use behaviour towards mobile payment applications. [9]. Tomic et al. [10] found that performance expectancy, perceived security, trust, and social influence have strong positive effects on behavioural intention to use electronic payment systems in Serbia. Giri [11] found that if users believe UPI is useful, easy to use, and see others using it, they're more likely to adopt it themselves. Regina [12] showed that if users find the services useful, easy to use, and influenced by others to try them, they're more likely to use these platforms, leading to greater satisfaction.

H1: There is a significant relationship between performance expectancy and behavioural intention.

B. *Effort Expectancy*

Effort expectancy is defined as the degree of ease people perceive in learning and using a new technology [7]. Winata [13] reveal that effort expectancy does not have a significant effect on continuance intention, suggesting that once users are accustomed to the technology, ease of use becomes less critical. Dagnoush [14] found that when users find mobile shopping apps simple and user-friendly, they're more likely to want to use them in Libya. Tsai [15] indicate that facilitating conditions significantly impact effort expectancy, which in turn affects users'

intention to adopt mobile payments. Musa [16] found that ease of use doesn't directly affect the decision to use mobile payment in Qatar, but it does matter when people believe the technology is useful. Factors like age, gender, and how much people think they know also affect these connections. Teo [17] found that effort expectancy significantly influences the intention to adopt mobile payments, highlighting the importance of perceived ease of use.

Hypothesis-H2: There is a significant relationship between effort expectancy and behavioural intention.

C. *Social Influence*

Social Influence is defined as a level of individual perceives that important others like friends, family, colleagues, or supervisors believe they should use a new system or technology [7]. H.A. Widyanto [18] found that social influence, among other things, directly affects people's intention to use mobile payment services in Indonesia. Ramesh [19] showed that social pressure from friends or society plays a key role in influencing their decision to make purchases through these apps. Bhatt [20] found that social influence, along with other factors, plays an important role in shaping users' intention to adopt mobile payment services.

Jin-Myong Lee [21] found that social pressure plays a big role in encouraging use, and gender influences how some of these factors interact in usage mobile payment services in South Korea. Tiago Oliveira [22] found that social influence strongly affects the decision to use mobile payments and the likelihood of recommending them to others in Portugal.

Hypothesis-H3: There is a significant relationship between Social Influence and behavioural intention.

D. *Facilitating Conditions*

Facilitating condition is defined as an individual believes that organizational and technical resources are available to support the use of a system or technology [7]. Linge [23] found that having the right support and resources positively affects people's intention to use mobile payment apps. Loncar [24] found that having the right support and confidence in using the technology makes it feel easier to use, which then increases how useful people expect it to be. Widyanto [25] found that having the right tools, resources, and support plays a key role in people's

decision to use mobile payments in Indonesia. R.K. Behera [26] Studied why some people choose not to use mobile payments and found that social factors and personal perceptions play a major role in that decision. Aik-Chuan Teo [27] found that factors like available support, usefulness, ease of use, and trust all strongly impact the decision to adopt mobile payments in Malaysia.

Hypothesis-H4: There is a significant relationship between facilitating conditions and behavioural intention

E. *Perceived Trust*

Trust is the belief that you can rely on someone's words, actions, and decisions with confidence [28]. In NFC based research, M. Alrawad [29] found that different types of trust strongly influence user decisions. Establishing trust helps reduce perceived risks and encourage adoption. In another study, Widyanto H [30] concluded that trust is a key determinant of whether someone will adopt the services. Afef Sahli Sassi [31] found that lower perceived risk and stronger security features build trust, which then boosts users' willingness to use mobile payments. Elbasir [32] found that trust, security, and reliability are key areas of issue for both the businesses and the customers. Improving these areas are essential to increase the use of such systems. Shalini Chandra [33] concluded that trust in both the service provider and the technology is crucial for people to start using mobile payment systems.

Hypothesis-H5: There is a significant relationship between perceived trust and behavioural intention

F. *Perceived Risk*

Perceived risk is defined as the fear that customers might leave if they feel the service could cause issues or considered as unsafe [34]. Eugene Bland [35] found that performance and psychological risks significantly discourage acceptance. The research highlights the negative impact of these concerns on adoption. Minh-Tri Ha [36] studied about explored various perceived risk factors influencing mobile payment usage in Vietnam, emphasizing the importance of addressing these risks to enhance user adoption. Wei-Lun Chang [37] emphasizes concerns about performance and security risks as major factors influencing mobile payment adoption. Noopur

Saxena [38] identifying perceived privacy risk as the most critical barrier in mobile banking adoption in India. Rajeev Thakur [39] found that perceived risk negatively impacts usage, with variations across customer groups.

Hypothesis-H6: There is a significant relationship between perceived risk and behavioural intention.

G. *Perceived Cost*

Perceived Cost is defined as how expensive or demanding people think something will be—whether in money, time, or effort. Perceived cost (PC) refers to the extent to which M-payment consumers believe that using technology will cost them a lot of money [40]. Costs can come from things like paying a subscription, buying the device, or covering internet charges to download the apps [41]. Abdelkader M. A. Mobarak [42] found that perceived high costs stop people from using mobile payment services. The study stresses that reducing cost concerns can help increase adoption. Hendrik A. Widyanto [43] updated the UTAUT model by adding security, risk, and trust to better explain mobile payment adoption. While cost wasn't directly studied, related risks were found to strongly affect users' intentions. Kuo-Yu Lin et al. [44] examined how perceived costs influence users' perceived value and, subsequently, their intention to use mobile payment services. Wan-Rung Lin [45] studied what affects Taiwanese consumers' decision to use mobile payments. The research showed that high perceived costs lower people's willingness to adopt these services, stressing the need for more affordable options. Koenig-Lewis [46] studied and improved the UTAUT model by including security, risk, and trust to better understand mobile payment adoption. Although cost wasn't directly measured, related risks had a strong impact on users' intention. Some studies on M-payment adoption suggest that higher perceived costs discourage people from using mobile payment services. [47] [48]

Hypothesis-H7: There is a less significant relationship between perceived cost and behavioural intention.

H. *Behavioural intention*

Behaviour Intention is defined as conscious plans to perform or not perform a specific future behaviour. Chandrasekar, [49] studied how Gen Z in Malaysia

feels about using digital payments. The research showed that high costs discourage them, while convenience, trust, and security make them more likely to use digital payments. Islam M [50] looked at what influences people in Bangladesh to use QR mobile payments. The study found that usefulness, ease of use, and social influence are key factors in their decision to adopt it. Singh S. S [51] explored what drives Indian merchants to use third-party mobile payment apps like Paytm and Google Pay. The study found that trust, perceived cost, ease of use, and experience all strongly influence their decision. Nirmawan [52] studied small traders' willingness to use Go-Pay in Indonesia. The study discovered that trust and perceived cost are significant factors in their decision to use the Go-Pay app by small traders in Indonesia. Sharma, [53] examined how factors like ease of use, security, usefulness, and cost influence customers' intention to use mobile wallets such as Paytm, Free Charge, and Mobi Kwik.

II. METHODOLOGY

This study utilized a quantitative research approach to analyse the effectiveness of TPPA. This study employed the purposive sampling technique to collect the samples. The primary data were collected through a survey instrument in the form of a questionnaire. The questionnaire was constructed according to the research objectives. Data were collected through a Google form, and 572 sample responses were received. A secondary data source was used to review the literature.

III. DATA ANALYSIS

Internal consistency is assessed using Cronbach's Alpha and composite reliability. All constructs in the model exceed the acceptable threshold of 0.70 for Cronbach's Alpha, confirming good reliability. Additionally, it generates sensitivity to the scale items and evaluates that all indicators' outer loadings are consistent. Consequently, it would be a study limitation when calculating the Cronbach's alpha. To get around the limitation, many researchers recommended measuring composite reliability. Like Cronbach's alpha, composite reliability in a measurement model addresses the internal consistency of the scale items without constraints. The findings support the conclusion that the observed

indicators reliably measure their constructs and provide a strong basis for assessing the structural relationships in the model.

Table 1 Demographic Profile of the respondents

Variable	Category	Frequency	(%)
Gender	Male	365	63.8
	Female	207	36.2
Age	Below 18	29	5.1
	18–25	229	40.0
	26–35	197	34.5
	36–45	72	12.6
	Above 45	45	7.9
Income (₹)	Below 20,000	57	10.0
	20,001–40,000	229	40.0
	40,001–60,000	171	29.9
	Above 60,000	115	20.1
Education	High School	63	11.0
	Diploma	63	11.0
	Undergraduate	229	40.0
	Postgraduate	172	30.1
	PhD	45	7.9
Area	Rural	86	15.0
	Semi-Urban	143	25.0
	Urban	343	60.0
Occupation	Student	114	19.9
	Business	143	25.0
	Government Employee	56	9.8
	Private Employee	201	35.2
	Unemployed	58	10.1
Primary TPPA App	Google Pay	190	33.2
	PhonePe	182	31.8
	Amazon Pay	114	19.9
	Others	86	15.0

Source: Primary Data computed using SPSS24

Table 1 shows the demographic profile of the respondents. Out of 572 respondents, 63.8% were male and 36.2% female. The majority were aged 18–25 (40%) and 26–35 (34.5%), indicating higher TPPA usage among young adults. Most earned between ₹20,001 and ₹40,000 per month (40%), and undergraduates (40%) and postgraduates (30.1%) formed the largest educational groups. Urban

residents dominated (60%) in area of residence. Private employees (35.2%) and business owners (25%) were the main occupational categories. In case of primary application usage, Google Pay (33.2%) and PhonePe (31.8%) were the most commonly used apps. Overall, the data suggest that young, educated, urban, and middle-income individuals are the primary users of third-party payment aggregators in India.

Table 2 Measurement Model

	Cronbach's alpha Values	CR Values	AVE Values
Behavioural intentions	0.777	0.812	0.591
Effort Expectancy	0.781	0.796	0.603
Facilitating Conditions	0.751	0.761	0.571
Perceived Cost	0.761	0.751	0.568
Performance expectancy	0.889	0.760	0.720
Perceived Risk	0.740	0.751	0.562
Perceived Trust	0.800	0.804	0.624
Social Influence	0.767	0.770	0.590

Source: Primary Data computed using SmartPLS4

As presented in Table 2, existing literature, especially the work by Hair J.F [54], suggests that the Cronbach's Alpha value for each construct should be above the 0.700 threshold to demonstrate internal consistency. In addition, composite reliability (ρ_a) is also expected to be above 0.700 but is sometimes considered acceptable for exploratory research with values falling between 0.600 and 0.700. In this study all constructs pass the minimum requirement for both Cronbach's Alpha and composite reliability, demonstrating solid construct reliability and internal consistency. The Cronbach's Alpha values for this study vary from a low of 0.740 to a high of 0.889, with Performance Expectancy (0.889) measuring the highest reliability, while Perceived Risk (0.740) measured the lowest. Likewise, composite reliability values (ρ_a) vary from a low of 0.751 to a high of 0.812, with Behavioural Intentions (0.812) measuring the higher composite reliability, while Perceived Cost (0.751) measured the lowest. These values demonstrate that each construct possesses a reliable internal structure and indicates anything represented by items will consistently represent the latent variables they were designed to measure.

Convergent validity, as measured by Average Variance Extracted (AVE), is critical to establishing that all items under a construct share a common underlying factor. Hair Jr. [55] recommends a threshold of 0.500 for AVE. In this study, AVE values range from 0.562 to 0.720, with the lowest recorded for Perceived Risk (0.562) and the highest for Performance Expectancy (0.720). All AVE values meet the recommended criteria, supporting the conclusion that the constructs exhibit sufficient convergent validity. Furthermore, while it is not shown here, the model would also demonstrate discriminant validity if the square roots of the AVE (average variance extracted) of each construct were larger than the correlations between the constructs in the model - further affirming that each construct is measuring a distinct concept. Discriminant validity refers to the degree to which measures of distinct constructs are indeed distinguishable and does not share measurement overlap. Discriminant validity is critical when working with multiple constructs as a lack of discriminant validity can create a false relationship among the variables.

Table 3 Results of Hypothesis Testing

H	Relationship	SD	T-test	P-value	Decisions
H1	PE -> BI	0.047	0.497	0.619	Not supported
H2	EE-> BI	0.062	6.870	0.000	Supported
H3	SI -> BI	0.073	7.776	0.000	Supported
H4	FC-> BI	0.071	0.760	0.447	Not supported
H5	PT -> BI	0.059	0.232	0.816	Not supported
H6	PR -> BI	0.057	1.796	0.043	Supported
H7	PC -> BI	0.058	1.316	0.188	Not supported

Source: Primary Data computed using SmartPLS4

*H-Hypotheses, PE- Performance Expectancy, EE- Effort Expectancy, SI- Social Influence, FC- Facilitating Condition, PT- Perceived Trust, PR- Perceived Risk, PC- Perceived Cost

Table 3 shows the test results show that out of 7 hypotheses suggested for SEM, three hypotheses support the research model. Variables like effort expectancy, perceived risk, and social influence significantly impact behavioural intention. Especially, Behavioural Intention has a positive influence on social influence. However, variables like facilitating conditions, perceived cost, performance expectancy,

and perceived trust do not significantly influence Behavioural Intention. Effort expectancy accepted the decision regarding the hypothesis. These test results show that Effort Expectancy significantly impacts behavioural intention ($t=6.870, p=0.000$) which below 0.05. This indicates a strong, statistically significant positive effect of Effort Expectancy on Behavioural Intentions. Thus, H2 was accepted. Social Influence was statistically significant and influenced behavioural intention ($t=7.776, p=0.000$) which is below 0.05. This indicates a strong positive effect of Social Influence on Behavioural Intentions thus, H3 was accepted. Perceived Risk was statistically

significant and influenced behavioural intention ($t=1.796, p=0.043$) which is below 0.05. This indicates perceived risk significantly positively influenced Behavioural Intentions. Thus, H6 was accepted. Facilitating conditions accepted the decision regarding the hypothesis. These test results shows that facilitating conditions significantly impact Behavioural Intention ($t=0.760, p= 0.447$) which is greater than 0.05. This indicates that Facilitating Conditions have a better effect on Behavioural Intentions. Therefore, H4 was supported. Perceived Cost accepted the decision regarding the hypothesis. These test results show that Perceived Cost do not significantly impact Behavioural Intention ($t= 1.316, p= 0.188$) which is greater than 0.05. This indicates

that Perceived Cost does not significantly influence Behavioural Intentions. Hence, H7 is supported. Performance Expectancy rejected the decision regarding the hypotheses. These test results show that performance expectancy does not significantly impact Behavioural Intention ($t= 0.497, p= 0.619$) which is greater than 0.05. Thus, H1 was not supported. Perceived Trust, rejected the decision regarding the hypotheses. In these test results, Perceived Trust did not statistically significantly influence behavioural intention ($t= 0.232, p=0.816$) which is above 0.05. This indicated that Perceived Trust does not mostly influence Behavioural Intentions. Thus, H5 was not supported.

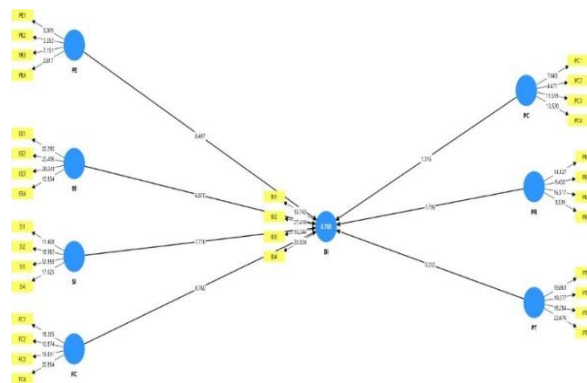


Fig 1 Structural Equation Modeling

Table 4 Discriminant validity (HTMT Ratio)

	BI	EE	FC	PC	PE	PR	PT
BI							
EE	0.834						
FC	0.778	0.703					
PC	0.595	0.467	0.865				
PE	0.281	0.120	0.151	0.230			
PR	0.492	0.497	0.699	0.760	0.054		
PT	0.628	0.497	0.884	0.796	0.114	0.532	

Source: Primary Data computed using SmartPLS4

*BI- Behaviour Intention, EE- Effort Expectancy, FC- Facilitating Condition, PC- Perceived Cost, PE- Performance Expectancy, PR- Perceived Cost, PT- Perceived Trust, SI- Social Influence

Above Table 4 shows that most of the HTMT values fall below the threshold of 0.85, confirming acceptable discriminant validity among the constructs. Although these values fall well below the more liberal cut-off of 0.90, it may indicate a more conceptual relationship between the two constructs, and it may be worth further theoretical justification

or confirmatory analysis. The HTMT analysis confirms that the constructs used in this model are sufficiently distinct and do not significantly overlap, thus supporting the reliability of the measurement model.

V. DISCUSSION

The findings of this study shows that Effort expectancy, perceived risk, and social influence play a crucial role in shaping behavioural intention to adopt third-party payment aggregators in India. They directly influence the trust, confidence and

convenience of the users. Social influence has highest impact in collective and community-driven culture of India. The recommendations from peers, family, and social networks increase confidence in trying new financial technologies like Google pay, Phonepe etc., Effort expectancy acts as a second most important variable to affect behaviour intention. The people especially those new to digital payments are more likely to adopt a payment aggregator due to its simple, reliable and its minimal learning effort. Perceived risk is another important factor has a positive influence as financial security and privacy concerns strongly influence adoption decisions. The users are more willing to engage with the service once they feel their money and data are protected. On other hand, Facilitating conditions, perceived cost, performance expectancy and perceived trust does not have a significant influence on behavioral intention to adopt third-party payment aggregators in India. Because, these factors are either already normalized or outweighed by more pressing concerns. Perceived cost does not strongly impact intention because most payment aggregators offer free or negligible-cost services. So, users rarely consider expenses as a barrier. Similarly, Facilitating conditions like internet access, smartphone availability and technical support have improved drastically across India due to government initiatives and affordable data plans. It makes them less of a differentiating factor in adoption decisions. Performance expectancy also has a less influence over behaviour intention. The digital payment systems are already expected to work efficiently. So, nowadays users take speed and reliability for granted rather than viewing them as special advantages. Perceived trust has very less significant influence on behavioural intention. This is because trust is often built indirectly through social influence and regulatory assurances rather than acting as a primary motivator from the start

VI. CONCLUSION

This research highlights the transformational role of TPPAs in bridging the divide between trust and technology in India. Young, urban populations are ready to embrace TPPAs, while barriers due to perceived risk, unfamiliarity, and infrastructure issues still limit adoption in rural and semi-urban populations. If TPPAs are able to address the issues preventing adoption like improved security; education

about risks, rewards, and use; prices or fees; etc., then they could potentially facilitate better financial inclusion and increase digital literacy. The findings support the trend in the global acceptance of digital payments, however, this research shows the need for a concentrated effort to better address the various demographics. Continued research may look at the longitudinal nature of TPPAs towards adoption; or the learnings from finance and emerging technologies (e.g., blockchain) on TPPA ecosystems. Finally, the development of connections and conversations between regulators, fintech firms, and master communities should support the progression of digital payments in the regions.

ACKNOWLEDGMENT

I sincerely thank my students Ms.Trisha and Ms.Krishiga for their contribution of their data collection and various supports.

References

1. Afef Sahli Sassi, H. H. (2022). Perceived Risk, Structural Assurance and Trust in Mobile Payments. *Journal of Telecommunications and the Digital Economy*, 41–56.
2. Aik-Chuan Teo, G. W.-H. (2015). Why Consumers Adopt Mobile Payment? A Partial Least Squares Structural Equation Modelling (PLS-SEM) Approach. *International Journal of Mobile Communications*.
3. Alqahtani, A.-B. P. (2014). Exploratory study of m-transaction: user's perspectives. *Electron. J. Inf. Syst. Dev. Ctries.*, 60(1), 1-22.
4. Astiwardhani, N. &. (2021). The effect of perceived cost, trust, usefulness, and customer value addition on intention to use Go-Pay mobile payment services. *Journal of Business and Management Review*, 715–732.
5. Behera, P. B. (2022). Safety First: Extending UTAUT to Better Predict Mobile Payment Adoption by Incorporating Perceived Security, Perceived Risk, and Trus. *Journal: Journal of Science and Technology Policy Management*, 952–973.
6. Bhatt, P. P. (2020). Understanding Consumer Adoption of Mobile Payment in India: Extending Meta-UTAUT Model with Personal Innovativeness, Anxiety, Trust, and Grievance Redressal. *International Journal of Information Management*.
7. Chandrasekar, K. &. (2024). Determinants of digital payment adoption among Generation Z. *Journal of Risk and Financial Management*, 521.

8. Dagnoush. (2021). The Effect of Users' Effort Expectancy on Users' Behavioral Intention to Use M-Commerce Applications: Case Study in Libya. *International Journal on Recent Trends in Business and Tourism*, 1–8.
9. Elbasir, M. E. (2020). The Influence of Trust, Security, and Reliability of Multimedia Payment on the Adoption of EPS in Libya. *Multicultural Education*, 1–12.
10. Eugene Bland, C. C. (2024). Investigating the Components of Perceived Risk Factors Affecting Mobile Payment Adoption. *Journal of Risk and Financial Management*.
11. Featherman, a. P. (2003). Predicting e-services adoption: a perceived risk facets perspective. *Int. J. Hum. Comput. Stud.* 59,, 451–474.
12. Giri, A. &. (2022). Factors driving the adoption of UPI services based on UTAUT model. *International Journal of Management*, 45–58.
13. H.A. Widyanto, K. K. (2022). Safety First: Extending UTAUT to Better Predict Mobile Payment Adoption by Incorporating Perceived Security, Perceived Risk, and Trust. *Journal of Science and Technology Policy Management*.
14. Hair Jr, J. F. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2),, 107-123.
15. Hair, J. F. (2014). A primer on partial least squares structural equation modeling (PLS-SEM). SAGE.
16. Hendrik A. Widyanto, K. A. (2022). Safety First: Extending UTAUT to Better Predict Mobile Payment Adoption by Incorporating Perceived Security, Perceived Risk, and Trusts. *Journal of Science and Technology Policy Management*, 952-973.
17. Islam M, T. A. (2023). The Path to Cashless Transaction: A Study of User Intention and Adoption of QR Mobile Payment. *PMC*.
18. Jin-Myong Lee, B. L. (2019). Determinants of Mobile Payment Usage and the Moderating Effect of Gender: Extending the UTAUT Model with Privacy Risk. *International Journal of Electronic Commerce Studies*.
19. Koenig-Lewis, N. M. (2015). Exploring the antecedents of mobile payment service usage: An empirical study based on perceived value and social influence perspective. *International Journal of Bank Marketing*, 744-761.
20. Kumar, H. &. (2024). Analysing consumer behaviour by integrating digital payment awareness into the UTAUT model. *International Journal of Electronic Finance*, 139-167.
21. Kuo-Yu Lin, Y.-T. W. (2020). Exploring the Antecedents of Mobile Payment Service Usage: Perspectives Based on Cost–Benefit Theory, Perceived Value, and Social Influences. *Online Information Review*, 299–318.
22. Linge. (2023). Analysis of Factors Affecting Use Behavior towards Mobile Payment Apps: A SEM Approach. *Human Behavior and Emerging Technologies*.
23. Loncar, L. L. (2022). Mobile Payment Adoption at the Pre-Purchase Stage. *International Journal of Mobile Communication*.
24. Luarn, H. L. (2005). Toward an understanding of the behavioral intention to use mobile banking,. *Comput. Hum. Behav.* 21 (6), 873–891.
25. M. Alrawad, A. L. (2023). Examining the Influence of Trust and Perceived Risk on Customers' Intention to Use NFC Mobile Payment system. *Journal of Open Innovation: Technology, Market, and Complexity*.
26. McAllister, D. J. (1995). Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of management journal*, 38(1), 24-59.
27. Minh-Tri Ha, K.-T. T. (2024). Understanding Perceived Risk Factors Toward Mobile Payment Usage by Employing Extended Technology Continuance Theory: A Vietnamese Consumers' Perspective. *Journal of Asia Business Studies*.
28. Mobarak, A. M. (2024). Drivers of Mobile Payment Services Adoption: A Behavioral Reasoning Theory Perspective. *International Journal of Human–Computer Interaction*,, 1518-1531.
29. Musa, A. K. (2015). Factors Influence Consumers' Adoption of Mobile Payment Devices in Qatar. *International Journal of Mobile Communications*, 13(6), 670–689.
30. Noopur Saxena, N. G. (2020). Exploring the Effect of Perceived Risk on Adoption of Mobile Banking in India. *International Journal of Public Sector Performance Management*.
31. NPCI. (2025). Unified Payments Interface (UPI). Retrieved from <https://www.npci.org.in/what-we-do/upi/product-overview>
32. PWC. (2024, August). The Indian Payments Handbook 2024-2029. (Price Water Cooper) Retrieved from https://www.pwc.in/assets/pdfs/indian-payment_handbook-2024.pdf
33. Qingfei, S. G. (2008). Mobile commerce UserAcceptance study in China- A revised UTAUT model. *Tsinghua Sci. Technol.* 13 (3), 257–264.
34. Rajeev Thakur, M. S. (2014). Adoption Readiness, Personal Innovativeness, Perceived Risk and Usage Intention Across Customer

- Groups for Mobile Payment Services in India. *Internet Research*, 369–392.
35. Ramesh, S. R. (2022). Study on the Acceptance of Mobile-Banking Applications in India— Unified Theory of Acceptance and Sustainable Use of Technology Model (UTAUT). *Sustainability*.
 36. Razorpay. (2024, November 19). What is a Payment Aggregator? Meaning, Example, Types and How It Works . (Razorpay Blog) Retrieved from <https://razorpay.com/blog/what-is-a-payment-aggregator>
 37. Regina, T. K. (2021). UTAUT approach application to analyze the determinants of fintech market aggregator user satisfaction. *First International Conference of Economics, Business & Entrepreneurship*.
 38. Santana, T. (2025, June 3). India: 2025 analysis of payments and ecommerce trends. (PCMI) Retrieved from <https://paymentscmi.com/insights/india-2025-ecommerce-payments-trends/>
 39. Shalini Chandra, S. C.-L. (2010).) Evaluating the Role of Trust in Consumer Adoption of Mobile Payment Systems: An Empirical Analysis. *Communications of the Association for Information Systems*.
 40. Sharma & Sharma, M. (2019). Factors affecting behavioral intention to use mobile wallets in India. *Journal of Advances in Management Research*, 472–497.
 41. Sing, S. a. (2024). Digital banking: It's role, impact & challenges. *International Journal of Research in Finance and Management*, 7(1), 579-584.
 42. Singh, M. (2023). Analysis of factors affecting use behavior towards mobile payment apps A SEM approach. *Human Behavior and Emerging Technologies*.
 43. Singh, S. S. (2022). Moderating and mediating effect of perceived experience on merchant's intention to use mobile payment services. *Frontiers in Psychology*.
 44. Stripe. (2023, July 27). What is a payment aggregator? Here's what they are and how they enable online payments . (Stripe Payments) Retrieved from <https://stripe.com/in/resources/more/payment-aggregators-101>
 45. Teo, A. C. (2015). Why Consumers Adopt Mobile Payment? A Partial Least Squares Structural Equation Modelling (PLS-SEM) Approach. *International Journal of Mobile Communications*, 13(5), 478–497.
 46. Teo, T. K. (2015). Why consumers adopt mobile payment? A partial least squares structural equation modelling (PLS-SEM) approach. *Int. J. Mobile Commun.* 13 (5), 478.
 47. Tiago Oliveira, J. G. (2016). Mobile Payment: Understanding the Determinants of Customer Adoption and Intention to Recommend the Technology. *Computers in Human Behavior*.
 48. Tomić, N. K. (2022). Using the UTAUT model to analyze user intention to accept electronic payment systems in Serbia. *Port Economic Journal*, 251–270.
 49. Tsai, L. L. (2021). Evaluating the Effects of Facilitating Conditions and Usage Experience on Mobile Payment. *International Journal of Information Systems in the Service Sector*, 13(4), 1–17.
 50. Venkatesh, V. M. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.
 51. Wan-Rung Lin, C.-Y. L. (2020). Factors Affecting the Behavioral Intention to Adopt Mobile Payment: An Empirical Study in Taiwan. *Mathematics*.
 52. Wei-Lun Chang, R. P. (2023). The Role of Perceived Risks on Mobile Payment Adoption: Evidence from Asia. *International Journal of Mobile Communications*, 249-272.
 53. Widyanto, H. (2022). Extending UTAUT to Better Predict Mobile Payment Adoption by Incorporating Perceived Security, Perceived Risk, and trust. *Journal of Science and Technology Policy Management*, 952-973.
 54. Widyanto, H. K. (2022). Safety First: Extending UTAUT to Better Predict Mobile Payment Adoption by Incorporating Perceived Security, Perceived Risk, and Trust. *Journal of Science and Technology Policy Management*, 13(4), 952–973.