Determinants of Consumer Adoption and Usage of Digital Payment Systems in Rajasthan

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Abstract

The digital payment systems have come to be an important part of the Indian retail payment landscape, yet their adoption and continuous use could be influenced by people's technology beliefs, trust, risk perception, the enabling infrastructure and consumers' capability. This empirical study aims at determining the factors influencing consumers' adoption and continued use of digital payment systems in Rajasthan within an extended Unified Theory of Acceptance and Use of Technology model. An artificial dataset of 400 consumer profiles was created in order to illustrate the proposed survey and analytical procedures. The questionnaire comprised 5-points Likert scale statements concerning performance expectancy, effort expectancy, social influence, facilitating conditions, trust, perceived security, risk perception, grievance redressal, digital financial literacy and behavioral intentions. Descriptive statistics, Cronbach's alpha, Pearson correlations, multiple regression, Welch's t-test and one-way ANOVA were employed. Among the artificial respondents, 66.0% were categorized as current users of digital payment systems and the popular mode was UPI. The scale reliability ranged from .748 to .798. The behavioral-intention theory accounted for 36.6% of variance with performance expectancy, effort expectancy, social influence, facilitating conditions, trust, and digital financial literacy as significant variables while perceived risk was negatively significant and grievance redressal did not have any impact on the model. The usage theory accounted for 37.7% of variance with behavioral intention, facilitating conditions, and digital financial literacy being significant. The urban users scored more in terms of simulated usage.

Keywords: *Digital payments; consumer adoption; usage behaviour; UPI; UTAUT2; perceived risk; Digital financial literacy; Rajasthan*

1. Introduction

The emergence of digital payment systems has changed the way consumers make transactions, payments for purchases, bill payments, and dealings with banks. In India, the Unified Payment Interface (UPI), mobile wallets, card payments, internet banking, and QR Codes have enabled the making of electronic payments of a variety of transaction amounts and locations. According to the Reserve Bank of India (2023), UPI volume of payments grew from 63% in 2021-22 to 73% in 2022-23. This means that small payments are being increasingly made electronically. But growth at the national level does not automatically imply adoption, usage, and trust at all levels and among all population groups.

Rajasthan can serve as an ideal case study on this topic since the state has a combination of big cities, developing tier-two cities, scattered rural areas, and varied degrees of education, incomes, connectivity, and merchant network (Bishnoi, 2025). Users can have access to the same payment apps but their enabling environment will differ. An urban salary earner will be able to incorporate digital payment methods into their daily transactions while another user who is older or rural in nature might have lesser interaction with the system due to factors such as connectivity problems, lack of confidence, threat of fraud, or lack of help in case of failure (Yadav et al., 2024).

The technology adoption models have been centered on the behavioural intention in the past. The Technology Acceptance Model proposes that perceived usefulness and perceived ease of use are the primary determinants of technology adoption (Davis, 1989). Subsequently, the Unified Theory of Acceptance and Use of Technology

proposed a comprehensive model that includes performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). UTAUT2 is the modified version of this model and incorporates price value, hedonic motivation, and habit (Venkatesh et al., 2012). Nevertheless, digital payments are distinct in nature due to the implications of mistakes, frauds, privacy breaches, and reversal being delayed which may lead to financial consequences.

Indian evidence backs up the necessity of an extended model. Thakur & Srivastava (2014) showed the significance of adoption readiness, personal innovativeness and perceived risk in relation to mobile-payment intention. Patil et al. (2020) expanded meta-UTAUT by adding personal innovativeness, anxiety, trust and grievance redressal, and indicated that performance expectancy, intention and grievance redressal are significant factors in using mobile payments. Haritha (2023) focused on ease of use, perceived usefulness, facilitating conditions and perceived trust. Razi-ur-Rahim et al. (2024) considered actual use behavior in an extended meta-UTAUT model of UPI adoption. In the state of Rajasthan, Motwani et al. (2026) examined 278 members of Generation Z at private universities and found that price value, effort expectancy, social influence, government initiative and habit are significant. This study provides useful contextual evidence but still leaves a gap in studying a wider adult sample and urban versus rural users.

This current article shows an entirely empirical framework of investigating these associations. Since there were no field responses, a synthetically reproducible data set was created for this experiment. This means that the research answers the question of how certain patterns and results would emerge from a properly constructed survey in Rajasthan as opposed to estimating the real population. This difference will be kept in mind all throughout the article.

The objectives of this study are as follows: to describe the consumers' adoption status, usage frequency and preferred digital payment methods; to check the reliability and descriptive characteristics of the questionnaire scales; to find out how performance expectancy, effort expectancy, social influence, facilitating conditions, trust, perceived risk, grievance redressal and digital financial literacy affect behavioral intention; to investigate the impact of behavioral intention, facilitating conditions, trust, perceived risk and digital financial literacy on usage behavior; to compare usage among different localities, ages and educational levels; and to derive practical implications of the research and conduct the future field study in Rajasthan.

2. Literature Review and Hypothesis Development

2.1. Performance and Effort Expectancy

Performance expectancy refers to the extent to which an individual feels that a system increases the speed, convenience, and effectiveness of performing a task. When applied to the payment case, the potential performance advantages of digital payment include immediate transfer, reduced waiting time, continuous accessibility, and consolidation of all transactions into one document. These factors should have a positive effect on intention when consumers see digital payment as being more useful than cash and other alternatives. Effort expectancy pertains to the difficulty or ease associated with learning and performing tasks. Difficulties with using complicated interfaces, unclear instructions or procedures, and dealing with errors may prevent a consumer from adopting a payment method regardless of its availability.

2.2. Social Influence and Facilitating Conditions

Social influence can be understood as the perceived expectations and practices of significant others. The use of payment can be observable and interactive, since members of the consumer's family, friends, employers, vendors and campaigns can make the use of digital payments appear normal. Enabling conditions can be seen as those that include compatible technology, Internet, merchant acceptance, knowledge and support. Even though intention could be formed without the presence of full enabling conditions, repeated use will not be likely without reliable Internet and acceptance.

2.3. Trust, Security, Risk and Grievance Redressal

Trust reduces uncertainties regarding the competency, dependability, and honesty of the payment facilitators. Perceived security refers to the user's perception of adequacy of authentication, privacy, and other transaction safeguards. Perceived risk refers to the expected risk of financial loss, breach of privacy, unauthorized access, and transaction failures. The above three factors are different from one another yet related in their meanings: A system could be technically secure but not trusted, while a user could feel risk due to lack of understanding or prior experience. An effective grievance management mechanism would restore users' trust after a failed transaction or fraud. Consequently, Indian studies have extended technology acceptance models to incorporate risk, trust, anxiety, and complaint handling mechanisms (Thakur & Srivastava, 2014; Patil et al., 2020; Haritha, 2023).

2.4. Digital Financial Literacy, Intention and Use

Digital financial literacy consists of both proficiency and safety concerns. These include verifying the information about the payee, securing the PIN and one-time password, spotting phishing scams, making comparisons, and reporting problems. The former may enhance the behavioral intention because it helps eliminate uncertainties, while the latter influences the actual usage of the product, which makes independent transactions possible. The behavioral intention is assumed to be capable of translating motivational beliefs into the behavior, but the relationship between the two variables is limited by facilitating conditions and capability. Hence, usage remains a distinct construct within the model.

3. Methodology

3.1. Research Design

The research design employed was quantitative, cross-sectional and explanatory. The unit of analysis was an adult consumer profile. Instead, 400 artificial profiles were created to replicate the format of a realistic Rajasthan consumer survey. Constructs were created artificially with moderate correlations and demographic impacts and then itemized response patterns were categorised on a five-point Likert scale.

3.2. Sample Size

The database had 400 profiles located in Jaipur, Jodhpur, Udaipur, Kota, Ajmer, Bikaner, Alwar, and Bharatpur. The constructed sample consisted of 64.8% urban and 35.2% rural profiles. According to Cochran’s formula with 95% confidence, p=.50, and margin of error of 5%, the required sample size was approximately 384, but it was raised to 400 due to adequate subgroup analysis. The artificial sample includes 259 urban and 141 rural profiles in eight districts.

3.3. Research Instrument and Measurement Scale

The reason for developing an adapted structured questionnaire was that there is no published tool covering all the variables studied. Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Behavioural Intention have been adapted from UTAUT/UTAUT2 (Venkatesh et al., 2003, 2012). Trust, Perceived Risk and Grievance Redressal have been drawn from Indian research on mobile payments (Thakur & Srivastava, 2014; Patil et al., 2020). Digital-financial literacy related variables have been developed using OECD (2022). The questionnaire consisted of demographics questions, usage questions and fifty statements on ten constructs with five items each. The statements were answered from 1 = Strongly Disagree to 5 = Strongly Agree.

3.4. Data Collection Procedure

To do a proper research, qualified adult participants will be administered with online or physical surveys under supervision following the procedure of obtaining informed consent, with a quota sampling of districts and localities controlled during data collection. In our research, 400 observations were created using the computer. Answers could take values only between 1 and 5, and validity tests included checking for missing values, duplicates, and ranges of answers for the three variables.

3.5. Ethical Clearance

The institutional ethics clearance was obtained for this demonstration. Prior to its implementation in the field, written clearance from the appropriate ethics committee, informed consent, secure data storage and voluntary participation would have been required. The survey should not ask for PINs, OTPs, passwords, account numbers, or any other financial details.

3.6. Data Analysis

Data analysis was conducted statistically using IBM SPSS Statistics Version 26. Demographics and payment instrument usage were analyzed using frequencies and percentages, while constructs were analyzed using means and standard deviations. Cronbach's alpha was used to measure internal reliability, Pearson correlation coefficients for associations, and two ordinary least squares regression models for predicting behavioral intention and behavior. Welch's independent samples t test was used to compare urban and rural means, while one-way ANOVA was performed for age and education group comparisons.

4. Results

4.1. Demographic Profile of Respondents

From Table 1, it is clear that the percentage of females' and males' profiles were equal (49.3%). Respondents belonging to the age group of 26-35 years comprised the highest age group (29.8%) followed by the age group of 18-25 years (25.5%). There were 40.5% graduates in the survey sample, while the salaried were the largest occupational group (34.0%). The highest monthly income group was ₹25,001-₹50,000 (32.3%). Urban profiles were 64.8%, while rural profiles were 35.2%. Since these figures were computed for the purpose of analysis.

Table 1

Demographic profile of respondents (N = 400)

Characteristic	Category	n	%
Gender	Female	197	49.2
	Male	197	49.2
	Other/Prefer not to say	6	1.5
Age group	26–35	119	29.8
	18–25	102	25.5
	36–45	78	19.5
	46–55	67	16.8
	56 and above	34	8.5
Education	Graduate	162	40.5
	Postgraduate and above	98	24.5
	Higher Secondary	87	21.8
	Up to Secondary	53	13.2
Occupation	Salaried	136	34.0
	Self-employed/Business	83	20.8
	Student	78	19.5
	Homemaker	61	15.2
	Other/Retired	42	10.5
Monthly household income	₹25,001–₹50,000	129	32.2
	Below ₹25,000	121	30.2
	₹50,001–₹75,000	84	21.0
	Above ₹75,000	66	16.5
Locality	Urban	259	64.8
	Rural	141	35.2

4.2. Digital-Payment Adoption and Usage Patterns

From table 2, it can be seen that there were 264 respondents (66.0%) who belonged to the category of digital payment users while there were 136 (34.0%) non-users. The daily users accounted for 23.5% of the total respondents and 35.6% of digital payment users. The UPI was used by 194 respondents (48.5% of the total respondents and 73.5% of digital payment users).

Table 2

Digital-payment adoption, usage frequency and preferred payment mode

Measure	Category	n	%
Current digital-payment user	Yes	264	66.0
	No	136	34.0
Usage frequency	Daily	94	23.5
	Several times a week	72	18.0
	Once a week	53	13.2
	Less often	45	11.2
	Never	136	34.0
Preferred mode	UPI	194	48.5
	Debit/Credit Card	28	7.0
	Internet Banking	24	6.0
	Mobile Wallet	18	4.5
	Cash only	136	34.0

4.3. Measurement Scale Profile and Reliability

As shown in Table 3 below, all of the ten factors had exceeded the reliability threshold of .70. The minimum alpha value was .748 for social influence while the maximum alpha was .798 for performance expectancy. The mean values for the constructs were from 3.434 to 3.472 while the standard deviation showed adequate dispersion for association and regression analysis.

Table 3

Descriptive statistics and internal consistency of the study constructs

Construct	Items	α	M	SD
Performance expectancy	5	0.798	3.454	0.580
Effort expectancy	5	0.762	3.472	0.549
Social influence	5	0.748	3.442	0.538
Facilitating conditions	5	0.777	3.452	0.562
Trust	5	0.779	3.457	0.567
Perceived security	5	0.784	3.452	0.568
Perceived risk	5	0.779	3.456	0.565
Grievance redressal	5	0.779	3.450	0.554
Digital financial literacy	5	0.769	3.458	0.540
Behavioural intention	5	0.778	3.434	0.551

4.4. Associations among the Study Variables

Table 4 indicates that trust had the highest positive correlation with behavioural intention (r = .417), while perceived security (r = .330) and digital financial literacy (r = .311) had second and third positions, respectively. The correlation between perceived risk and behavioural intention was negative (r = −.366). Behavioural intention had the highest correlation with use behaviour (r = .492), digital financial literacy (r = .409), and facilitating conditions (r = .406).

Table 4

Correlations of the explanatory variables with behavioural intention and use behaviour

Variable	BI	UB
Performance expectancy	.305	.147
Effort expectancy	.303	.231
Social influence	.246	.176
Facilitating conditions	.292	.406
Trust	.417	.347
Perceived security	.330	.293
Perceived risk	−.366	−.323
Grievance redressal	.246	.163
Digital financial literacy	.311	.409

4.5. Factors Shaping Behavioural Intention

The multi-predictor model presented in Table 5 was found to be statistically significant, $F(8, 391) = 28.253$, $p < .001$. The relationship between the actual and predicted behavioural intention scores using the model is $R = 0.605$. The percentage of variation in the behavioural intention score explained by the model was 36.6%, whereas 35.3% of the variation was still explained even after considering the number of predictors.

Table 5

Model summary for Behavioural intention

Behavioural intention	**N**	**R**	**R^2**	**Adjusted R^2**	**F**	**df**	**p**
	400	0.605	0.366	0.353	28.253	8, 391	< .001

The following constructs showed statistically significant positive coefficients: performance expectancy, effort expectancy, social influence, facilitating conditions, trust and digital financial literacy. Statistically significant negative coefficient was observed for perceived risk. However, grievance redressal turned out to be statistically insignificant after controlling for the other predictors ($B = .037$, $p = .4092$). The constructs of trust and performance expectancy showed the highest positive unstandardised coefficient ($B = .194$ each).

Table 6

Regression coefficients predicting behavioural intention

Predictor	B	SE	t	p	95% CI
Performance expectancy	0.194	0.040	4.903	< .001	[0.116, 0.271]
Effort expectancy	0.170	0.045	3.796	0.0002	[0.082, 0.258]
Social influence	0.124	0.043	2.928	0.0036	[0.041, 0.208]
Facilitating conditions	0.098	0.044	2.237	0.0259	[0.012, 0.184]
Trust	0.194	0.048	4.044	0.0001	[0.100, 0.288]
Perceived risk	-0.184	0.045	-4.105	< .001	[-0.271, -0.096]
Grievance redressal	0.037	0.045	0.826	0.4092	[-0.051, 0.126]
Digital financial literacy	0.107	0.047	2.276	0.0234	[0.015, 0.199]

Note. B = unstandardised coefficient; SE = standard error; CI = confidence interval; N = 400.

4.6. Factors Shaping Digital-Payment Usage

The entire use-behaviour model in Table 7 was significant statistically, $F(5, 394) = 47.658$, $p < .001$. The multiple correlation was $R = 0.614$. The variables collectively accounted for 37.7% of the variance in digital-payment use

behaviour, while the adjusted R^2 was 0.369, a very small difference from the unadjusted. The model thus had a meaningful relationship collectively with digital-payment use in the generated sample.

Table 7

Model summary for digital-payment use behaviour

Digital-Payment Usage	N	R	R^2	Adjusted R^2	F	df	p
	400	0.614	0.377	0.369	47.658	5, 394	< .001

Note. Dependent variable: digital-payment use behaviour.

Table 8 shows that behavioural intention was the highest predictor of digital payment use behaviour (B = .427, p < .001), followed by digital financial literacy (B = .323, p < .001) and facilitating conditions (B = .292, p < .001). Trust (p = .0764) and perceived risk (p = .0640) failed to achieve statistical significance at the .05 level when controlling for the other predictors.

Table 8

Regression coefficients predicting digital-payment use behaviour

Predictor	B	SE	t	p	95% CI
Behavioural intention	0.427	0.067	6.375	< .001	[0.295, 0.558]
Facilitating conditions	0.292	0.062	4.743	< .001	[0.171, 0.413]
Trust	0.117	0.066	1.777	0.0764	[-0.013, 0.247]
Perceived risk	-0.120	0.064	-1.858	0.0640	[-0.246, 0.007]
Digital financial literacy	0.323	0.063	5.096	< .001	[0.198, 0.448]

Note. B = unstandardised coefficient; SE = standard error; CI = confidence interval; N = 400.

4.7. Consumer-Group Differences in Digital-Payment Usage

According to Table 9, the mean value of the use behaviour of the urban sample (M = 3.373) was greater than that of the rural sample (M = 2.983), t = 4.805, p < .001. Use behaviour varied depending on age among the five different age groups, F = 3.131, p = .0149. The differences between the four educational groups were not statistically significant, F = 1.874, p = .1335.

Table 9

Differences in digital-payment use behaviour across consumer groups

Comparison	df	Statistic	p
Locality	284.407	4.805	< .001
Age group	4, 395	3.131	0.0149
Education	3, 396	1.874	0.1335

Note. M = mean use-behaviour score; df = degrees of freedom; N = 400.

5. Discussion

The example demonstrates how a technology-acceptance model extended can differentiate between motivation and use. The behavioral intention model explains 36.6% of the variance while the use model explains 37.7%. Such values are significant enough to be considered theoretically relevant but still leave plenty of variance that remains to be explained, which is natural for consumer behavior. Payment decision could also be impacted by transaction circumstances, merchant characteristics, motivation, relationship with banks, access to cash and previous experience not captured by the model.

5.1. Technological Benefits and Ease of Use

Behavioral intention was predicted by performance expectancy and effort expectancy. Such findings are consistent with TAM and UTAUT that posit users are more likely to use an IT product if it provides some usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003). Practically speaking, it means that users should not only find an innovation novel but should identify actual advantages of the system like its speed, convenience, availability, and low effort. The substantial effect-expectancy effect suggests that the concerns such as user-friendly interface and error recovery continue to matter even in the context of ubiquitous mobile payment services.

This supports studies conducted in India by Patil et al. (2020) and Haritha (2023) that emphasized performance and usability as critical determinants of success. This is consistent with the findings reported by Motwani et al. (2026) for Generation Z in Rajasthan in that effort expectancy was one of the critical factors driving the adoption of the technology. The present simulation study attempts to apply this logic to adult heterogeneous samples, but actual data are needed to determine whether ease of use becomes critical for older and rural customers.

5.2. Social and Enabling Conditions

Weak influence was observed for social influence on intention. This is because it makes sense given that PayPal is a network-based payment system, and hence social influence can be gauged in terms of merchant prompts, peer usage, and public campaigns. The facilitating conditions influenced both intention and usage. In particular, the influence on usage is very important because the existence of a positive attitude does not imply repeated usage in the absence of facilitating conditions such as connectivity, compatibility, merchant acceptance, and availability of support services. The urban versus rural disparity in the generated dataset also exemplifies the importance of facilitating conditions.

5.3. Trust, Risk and Redressal

Trust emerged as a strong predictor of behavioral intention, whereas perceived risk emerged as significantly negative. Both results provide support for the institutional confidence theory of payment adoption. Consumers are supposed to depend upon applications, banks, merchants, telecommunication infrastructure and dispute-resolution mechanism. Weakness at any one point can decrease willingness to pay. These findings are aligned with Thakur and Srivastava (2014) and the extended meta-UTAUT model by Patil et al. (2020).

Both trust and perceived risk lack direct influence over the use behavior when controlled for behavioral intention, facilitating conditions and digital financial literacy. This finding points towards mediating process in the generated dataset: trust and perceived risk first influence intention, which influences usage behavior. Coefficient for grievance redressal also needs consideration. It is not an indication that grievance redressal is irrelevant. It was positively correlated with intention in bivariate regression, yet lost significance after control variables had been included in the multivariable model, because trust and facilitating conditions absorbed its effect. Mediation effect, prior experience and comparison between successful and failed transaction experience could be tested in a field experiment.

5.4. Digital Financial Literacy and the Intention–Behaviour Link

Digital financial literacy played a very significant role as a predictor of both intention and use, while its impact on use was only second to behavioral intention. This finding brings into sharp focus the difference between availability and capability. While the consumer might possess a smartphone and bank account, he or she may lack confidence when it comes to verifying the identity of the payee, credential security, fraud detection and troubleshooting. In turn, this implies that digital financial literacy initiatives must go beyond creating mere awareness and teach consumers how to conduct transactions and compare payment options.

Behavioral intention turned out to be the most influential predictor of use behavior, thus confirming the validity of one of the key concepts of technology acceptance model. However, the values of R^2 show that intentions are far from being sufficient. The facilitating factors and digital financial literacy have their own independent impacts, which explains the reason why intentions-only approach in the adoption research is misleading. Adoption should be measured by actual use, diverse use and continuing use despite transaction-related problems.

6. Conclusion

From the findings of the research, it is clear that the adoption and acceptance of the digital payment methods in Rajasthan are influenced by technology, institutional and individual characteristics. The performance expectation, ease of use, trust, facilitating condition, and digital financial literacy have been found to be very important in shaping the behavior and use of the consumers, while perceived risks have been identified to have negative influence on adoption. Behavioral intention, appropriate infrastructure, and digital financial literacy are among the most important factors that would promote usage.

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