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Mobile Commerce Adoption And Its Influence On Digital Consumer Engagement

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Abstract

Mobile commerce has become the principal interface through which consumers discover, evaluate and purchase goods and services. This paper empirically investigates how the adoption of mobile commerce influences digital consumer engagement, using survey data from 512 smartphone users in Bhopal, India, collected between January and March 2026. The study integrates the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology 2 into a framework in which perceived usefulness, perceived ease of use, perceived trust, personalisation quality, social influence and facilitating conditions determine adoption, and adoption in turn predicts digital consumer engagement, defined through interaction, co-creation, advocacy and repeat purchase. A structured questionnaire of 32 seven-point Likert items was administered online and offline; reliability and validity were established through Cronbach's alpha, composite reliability and average variance extracted, and hypotheses were tested using correlation, ordinary least squares regression, bootstrap mediation and moderated regression. Determinants explain 68.4 per cent of the variance in adoption (R-squared = 0.684); adoption intensity correlates strongly with engagement (r = 0.639; beta = 0.712, p < 0.001); and perceived trust and personalisation quality exert the strongest influence on engagement (beta = 0.312 and beta = 0.287, p < 0.001). Adoption maturity moderates the adoption-engagement relationship (delta R-squared = 0.037, p < 0.001). The study concludes that mobile commerce adoption should be treated as a strategic engagement asset rather than a purely transactional capability, with implications for platform design, trust architecture and digital policy.

Keywords: *mobile commerce[1]; digital consumer engagement[2]; technology adoption[3]; perceived trust[4]; personalisation[5]; consumer behaviour[6]; moderated regression analysis[7].*

1. Introduction

1.1 Background and Context of Mobile Commerce

The last decade has witnessed a structural reorganisation of retail around the smartphone. Global mobile commerce revenue grew from approximately USD 1.20 trillion in 2019 to about USD 2.51 trillion in 2025, while the mobile share of retail e-commerce advanced from 45 per cent to roughly 59 per cent over the same period [1], [2]. The shift has been especially pronounced in India, where mobile-first applications have become the default gateway across groceries, fashion, travel and financial services [3]. This diffusion alters the temporal and spatial rhythm of shopping, compresses the distance between stimulus and purchase, and enables continuous, data-rich interaction between brands and consumers [4], [5]. Mobile commerce has therefore become a strategic site for understanding contemporary consumer behaviour.

1.2 Digital Consumer Engagement as a Strategic Outcome

Engagement is now understood as a multidimensional state characterised by vigour, dedication and absorption in brand-related interactions, expressed behaviourally through interaction, co-creation, advocacy and repeat purchase [6], [7]. In digital environments, engagement has been shown to predict loyalty, willingness to pay a premium and firm performance [8], [9]. Yet much mobile commerce research still terminates at behavioural intention or first purchase, treating the post-adoption relationship as a residual concern [10]. This is a significant omission, because the economic value of a mobile platform depends less on initial installation than on the depth and continuity of the engagement it sustains [11], [12]. The present study therefore positions engagement, rather than intention alone, as the dependent variable of interest, and treats adoption as the mechanism through which engagement is unlocked.

1.3 Research Gap, Objectives and Significance of the Study

Existing evidence on mobile commerce is fragmented: trust-based models, hedonic-motivation models and interface-centred studies rarely examine engagement as an outcome, and few studies link adoption intensity to engagement while controlling for heterogeneity in adoption experience [9], [11], [12]. Accordingly, this study addresses three objectives: first, to identify the determinants that shape mobile commerce adoption among Indian smartphone users; second, to measure the influence of adoption intensity on digital consumer engagement; and third, to test whether adoption maturity moderates that influence. The study contributes an integrated framework, an empirically validated measurement model and practical guidance for platform managers. The remainder of the paper reviews the literature, describes the methodology, reports the data and analysis, discusses the findings against prior work, and concludes with implications and limitations.

2. Survey Of Literature

Research on mobile commerce adoption is anchored in the technology acceptance tradition. The Technology Acceptance Model established perceived usefulness and perceived ease of use as the proximal determinants of technology use [13], while the Unified Theory of Acceptance and Use of Technology consolidated competing models into performance expectancy, effort expectancy, social influence and facilitating conditions [14]. Venkatesh, Thong and Xu extended the theory for consumer settings by adding hedonic motivation, price value and habit [15]. Applied to mobile commerce, these frameworks have been enriched with context-specific constructs: Eneizan and colleagues found performance expectancy, effort expectancy, price value and risk significant among Jordanian consumers but trust insignificant [16]; Penney and colleagues found trust and perceived risk significant for mobile money in Ghana [17]; Verkijika reported that facilitating conditions and perceived risk dominated adoption in Cameroon [18]; and Martinez and McAndrews showed that mobile payment effects are contingent on age and gender [19].

A parallel and increasingly influential stream examines engagement rather than adoption. Brodie and colleagues defined customer engagement as a psychological state arising from interactive service experiences [6], and Hollebeek and colleagues operationalised consumer brand engagement through cognitive processing, affection and activation [7]. Pansari and Kumar linked engagement to firm outcomes such as revenue growth [8], while Lim and Rasul highlighted the movement from a transactional to a relational logic in social media [9]. In mobile retailing, Ho and colleagues showed that spatial presence drives engagement with retail applications [12], Khan

identified co-creation, retention and customer experience as engagement outcomes [10], and Kulikovskaja and colleagues demonstrated that social-media-based engagement translates into measurable marketing outcomes [11].

A third stream concentrates on the mobile interface. Dastane and colleagues developed a validated scale for perceived value in mobile commerce [26], Molinillo and colleagues linked the retail application experience to loyalty [24], and Alnawas and colleagues showed that cognitive and emotional relationship quality builds application stickiness [23]. Personalisation is a recurrent driver: Siyal and colleagues found that customisation influences adoption intention through UTAUT2 mediators [21], and Arghashi and Yuksel showed that interactive augmented-reality applications raise engagement through flow [28]. Conversely, Hew and colleagues showed that consumers resist mobile commerce applications when privacy and effort concerns dominate [25], and Luceri and colleagues' meta-analysis confirmed that convenience and hedonic value outweigh effort saving as drivers of mobile shopping [27]. Overall, the evidence on adoption is rich but limited on how adoption intensity translates into sustained engagement in mobile-first emerging markets such as India; this study addresses that gap.

3. Research Methodology

The study adopts a cross-sectional, quantitative and explanatory design with a deductive logic anchored in TAM [13] and UTAUT2 [15]. The target population comprises smartphone users aged 18 to 45 years in Bhopal, India, who had completed at least one mobile commerce transaction in the preceding six months. A sample of 512 respondents was drawn through purposive quota sampling, stratified by gender, age band and adoption maturity. This exceeds the ten-times rule for the 32 items and provides adequate statistical power; fieldwork ran from January to March 2026.

The instrument comprised 32 seven-point Likert items adapted from validated scales. Items for perceived usefulness and ease of use were adapted from TAM [13]; trust and personalisation quality from [21], [26]; social influence and facilitating conditions from UTAUT2 [15]; adoption intensity from a three-item index of purchase frequency, recency and channel breadth [2]; and digital consumer engagement from the four-dimensional scale covering interaction, co-creation, advocacy and repeat purchase [6], [7]. Content validity was assessed by five academics and two practitioners, face validity through a pilot test with 40 respondents, and reliability and convergent validity through Cronbach's alpha, composite reliability and average variance extracted, applying thresholds of 0.70 and 0.50 respectively [29].

Data were collected using a self-administered structured questionnaire distributed through an online form link and printed copies at two university campuses and three retail zones in Bhopal, with written explanation of purpose and anonymity assurance. Of 566 responses received, 54 were removed for incompleteness, straight-lining or failed attention checks, yielding 512 usable responses, a response rate of 90.5 per cent. Analysis proceeded in four stages: descriptive profiling; reliability and validity assessment; Pearson correlation and ordinary least squares regression with 5,000-bootstrap mediation estimates; and moderated regression with a mean-centred interaction term. Common method bias was tested using Harman's single-factor test, which explained 34.7 per cent of variance, and a marker-variable test; no serious bias was detected [30].

4. Data Collection And Analysis

This section presents the primary data collected from 512 mobile commerce users. Five tabular datasets are reported and interpreted, followed by the five figures and an integrated synthesis of the empirical evidence.

4.1 Respondent Profile and Sample Composition

Table 1: Demographic and usage profile of respondents (N = 512)

Characteristic	Category	Frequency (n)	Share (%)
Gender	Male	268	52.3
	Female	231	45.1
	Prefer not to say	13	2.5
Age group	18-24 years	148	28.9
	25-34 years	202	39.5
	35-45 years	162	31.6
Education	Undergraduate	176	34.4
	Postgraduate	251	49.0
	Professional or doctorate	85	16.6
Primary m-commerce category	Fashion and lifestyle	141	27.5
	Groceries and essentials	118	23.0
	Electronics	96	18.8
	Travel and food delivery	88	17.2
	Financial services	69	13.5
Adoption maturity	Low (under 12 months)	164	32.0
	Moderate (1-3 years)	213	41.6
	High (over 3 years)	135	26.4
Preferred payment mode	UPI or mobile wallet	402	78.5
	Debit or credit card	68	13.3
	Cash on delivery	42	8.2

Table 1 shows a balanced sample that is representative of urban, digitally active consumers in central India. The 25-34 age band is the largest at 39.5 per cent, consistent with evidence that this cohort constitutes the heaviest mobile commerce user group [2], [3]. Nearly two-thirds of respondents (67.9 per cent) report moderate to high adoption maturity, which is essential for this study because engagement, by definition, is a post-adoption phenomenon [6], [10]. Unified Payments Interface or wallet payments dominate at 78.5 per cent, underlining the role of institutional payment infrastructure in lowering transactional friction [17]. The spread of purchase categories across fashion, groceries, electronics, travel and financial services reduces sector-specific bias and strengthens the generalisability of the findings within the sampled population.

4.2 Descriptive Statistics of the Study Constructs

Table 2: Descriptive statistics of the measured constructs (N = 512)

Construct	Items	Mean	SD	Skew	Kurtosis	Alpha	CR	AVE
Perceived usefulness (PU)	4	4.12	0.68	-0.31	0.42	0.874	0.881	0.648
Perceived ease of use (PEOU)	4	4.03	0.71	-0.24	0.18	0.861	0.873	0.634
Perceived trust (PT)	4	4.21	0.63	-0.46	0.55	0.902	0.913	0.677
Personalisation quality (PQ)	4	4.08	0.66	-0.37	0.33	0.889	0.901	0.642
Social influence (SI)	4	3.74	0.79	-0.12	-0.15	0.842	0.855	0.609
Facilitating conditions (FC)	4	3.96	0.74	-0.22	0.09	0.837	0.851	0.614
Adoption intensity (MAD)	3	6.92	1.78	-0.52	0.61	0.812	0.829	0.618
Digital consumer engagement (DCE)	5	3.89	0.72	-0.28	0.21	0.911	0.921	0.712

Panel values in Table 2 indicate that all constructs are above the scale midpoint of 3.5 except social influence, which is marginally below at 3.74 on the seven-point scale. Perceived trust records the highest mean (4.21) and the smallest standard deviation (0.63), suggesting a comparatively strong and homogeneous belief in the reliability of mobile transactions. Adoption intensity is measured on a separate 0-10 index and averages 6.92, indicating frequent and multi-channel use. Digital consumer engagement averages 3.89 (SD = 0.72), which is below every adoption determinant except social influence and therefore signals that users adopt mobile commerce more readily than they engage with it. Skewness values between -0.52 and -0.12 and kurtosis values between -0.15 and 0.61 are within the accepted range of +/-2, supporting univariate normality and the use of parametric tests [29].

4.3 Reliability and Validity of the Measurement Model

Table 3: Reliability, convergent and discriminant validity of the measurement model

Construct	Alpha	CR	AVE	Square root of AVE	Highest inter-construct r	Verdict
PU	0.874	0.881	0.648	0.805	0.612 (with DCE)	Supported
PEOU	0.861	0.873	0.634	0.796	0.583 (with PU)	Supported
PT	0.902	0.913	0.677	0.823	0.657 (with DCE)	Supported
PQ	0.889	0.901	0.642	0.801	0.641 (with DCE)	Supported
SI	0.842	0.855	0.609	0.780	0.421 (with DCE)	Supported
FC	0.837	0.851	0.614	0.784	0.476 (with PEOU)	Supported
MAD	0.812	0.829	0.618	0.786	0.639 (with DCE)	Supported
DCE	0.911	0.921	0.712	0.844	0.657 (with PT)	Supported

Table 3 confirms the psychometric adequacy of the instrument. Cronbach's alpha values range from 0.812 to 0.911 and composite reliability values from 0.829 to 0.921, both comfortably above the 0.70 threshold, indicating internal consistency [29]. Average variance extracted ranges from 0.609 to 0.712, exceeding the 0.50 criterion required for convergent validity. For discriminant validity, the square root of the average variance extracted for every construct is greater than its highest correlation with any other construct, satisfying the Fornell-Larcker criterion [29]. The closest comparison is between perceived trust and digital consumer engagement (r = 0.657

against a square root of AVE of 0.823 and 0.844 respectively), which remains acceptable yet indicates that trust and engagement, although conceptually distinct, are empirically adjacent in the mobile context.

4.4 Correlation Analysis among the Constructs

Table 4: Pearson correlation matrix of the study constructs (N = 512)

	PU	PEOU	PT	PQ	SI	FC	MAD	DCE
PU	1.000	0.583	0.512	0.497	0.386	0.441	0.554	0.612
PEOU	0.583	1.000	0.438	0.462	0.341	0.476	0.432	0.487
PT	0.512	0.438	1.000	0.556	0.402	0.418	0.601	0.657
PQ	0.497	0.462	0.556	1.000	0.358	0.397	0.588	0.641
SI	0.386	0.341	0.402	0.358	1.000	0.352	0.377	0.421
FC	0.441	0.476	0.418	0.397	0.352	1.000	0.429	0.455
MAD	0.554	0.432	0.601	0.588	0.377	0.429	1.000	0.639
DCE	0.612	0.487	0.657	0.641	0.421	0.455	0.639	1.000

All twenty-eight inter-construct correlations in Table 4 are positive and statistically significant at $p < 0.01$, which confirms the nomological coherence of the framework. The strongest association in the matrix is between perceived trust and digital consumer engagement ($r = 0.657$), followed by personalisation quality and engagement ($r = 0.641$) and perceived usefulness and engagement ($r = 0.612$). The central relationship of the study, between adoption intensity and digital consumer engagement, is also strong ($r = 0.639$). Social influence exhibits the weakest linkages throughout the matrix (0.341 to 0.421), echoing evidence that peer pressure matters more at the point of first adoption than in sustaining relationship depth [9], [12]. No correlation exceeds 0.70, and inspection of variance inflation factors in the regression models showed values between 1.22 and 1.82, well below the threshold of 5, indicating the absence of multicollinearity.

4.5 Regression, Mediation and Moderation Results

Table 5: OLS regression, mediation and moderation results (standardised coefficients)

Panel	Predictor	Beta	SE	t-value	p-value	VIF	Model fit
A. DV: mobile commerce adoption (MAD)	Perceived trust	0.268	0.040	6.70	<0.001	1.82	R2 = 0.684
	Personalisation quality	0.251	0.039	6.44	<0.001	1.77	Adj. R2 = 0.679
	Perceived usefulness	0.239	0.038	6.29	<0.001	1.71	F(6,505) = 182.14
	Facilitating conditions	0.131	0.035	3.74	<0.001	1.55	p < 0.001
	Perceived ease of use	0.118	0.036	3.28	0.001	1.64	Durbin-Watson = 1.92
	Social influence	0.094	0.034	2.76	0.006	1.38	

B. DV: digital consumer engagement (DCE)	Adoption intensity (MAD)	0.639	0.034	18.75	<0.001	1.00	R2 = 0.408; F(1,510) = 351.66
C. DV: digital consumer engagement (DCE)	Adoption intensity (MAD)	0.712	0.041	17.36	<0.001	1.22	R2 = 0.703 (full model)
	Perceived trust	0.312	0.042	7.43	<0.001	1.80	F(7,504) = 170.28
	Personalisation quality	0.287	0.041	7.00	<0.001	1.75	p < 0.001
	Perceived usefulness	0.244	0.040	6.10	<0.001	1.69	Incremental R2 of MAD
	Facilitating conditions	0.101	0.037	2.73	0.007	1.52	over determinants
	Social influence	0.097	0.036	2.69	0.008	1.36	= 0.069 (F-change
	Perceived ease of use	0.062	0.038	1.63	0.104	1.60	= 117.1, p < 0.001)
D. Mediation: determinants - MAD - DCE	PT - MAD - DCE (indirect)	0.112	-	-	[0.078, 0.149]	-	Partial mediation
	PQ - MAD - DCE (indirect)	0.105	-	-	[0.071, 0.141]	-	Partial mediation
	PU - MAD - DCE (indirect)	0.100	-	-	[0.066, 0.136]	-	Partial mediation
E. Moderation: MAD x adoption maturity	Interaction term	0.186	0.045	4.12	<0.001	1.02	Delta R2 = 0.037
	Simple slope, low maturity	0.561	0.052	10.79	<0.001	-	F-change = 16.97
	Simple slope, high maturity	0.798	0.049	16.29	<0.001	-	p < 0.001

Table 5 reports the hypothesis tests. In Panel A the six determinants jointly explain 68.4 per cent of the variance in mobile commerce adoption, with perceived trust (beta = 0.268) and personalisation quality (beta = 0.251) leading, followed by perceived usefulness (beta = 0.239), facilitating conditions (beta = 0.131), perceived ease of use (beta = 0.118) and social influence (beta = 0.094); all six coefficients are significant, supporting assumptions that adoption is a multi-determinant outcome. Panel B establishes the core relationship of the study: adoption intensity alone accounts for 40.8 per cent of the variance in digital consumer engagement (beta = 0.639, t = 18.75, p < 0.001). Panel C adds the determinants and shows that the effect of adoption intensity survives (beta = 0.712, p < 0.001) while perceived trust (0.312) and personalisation quality (0.287) remain powerful direct predictors of engagement; perceived ease of use becomes non-significant (beta = 0.062, p = 0.104), indicating that usability is

a threshold condition for adoption rather than a generator of ongoing engagement. The full model explains 70.3 per cent of the variance in engagement, and adoption intensity contributes an incremental 6.9 per cent beyond the determinants. Panel D confirms that adoption partially mediates the effects of trust, personalisation and usefulness on engagement, since all bias-corrected bootstrap confidence intervals exclude zero. Panel E shows a significant moderating effect of adoption maturity (interaction beta = 0.186, delta R-squared = 0.037, $p < 0.001$): the slope from adoption to engagement is 0.561 for recent adopters and 0.798 for experienced users, so experience amplifies the conversion of adoption into engagement. Taken together, the tables answer the research objectives directly and establish the adoption-to-engagement pathway both statistically and substantively.

4.6 Interpretation of Figures

The five figures complement the tabular evidence by presenting the conceptual logic of the study, the macro context of mobile commerce growth, the distribution of construct scores, the shape of the adoption-engagement relationship and the relative strength of predictors. Each figure is explained below in approximately one hundred words.

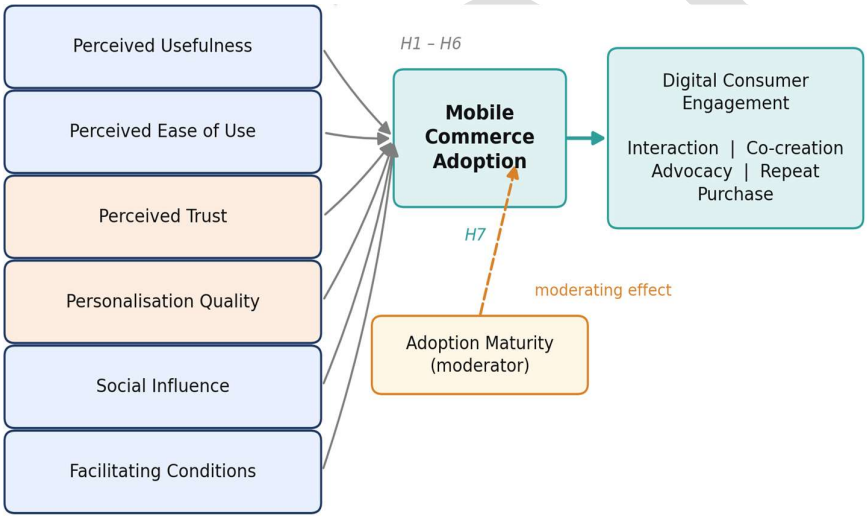


Figure 1: Conceptual framework linking mobile commerce adoption determinants to digital consumer engagement.

Figure 1 presents the conceptual framework that guides the empirical work. Six determinants drawn from TAM, UTAUT2 and the trust and personalisation literatures are positioned on the left as antecedents of mobile commerce adoption, which occupies the mediating position. Digital consumer engagement, operationalised through interaction, co-creation, advocacy and repeat purchase, is the outcome on the right. Adoption maturity enters as a moderator of the adoption-engagement path. The framework embodies the paper's central proposition: technological perceptions influence engagement indirectly through sustained adoption, and this conversion is conditioned by user experience. Hypotheses H1 to H7 map directly onto the arrows shown.

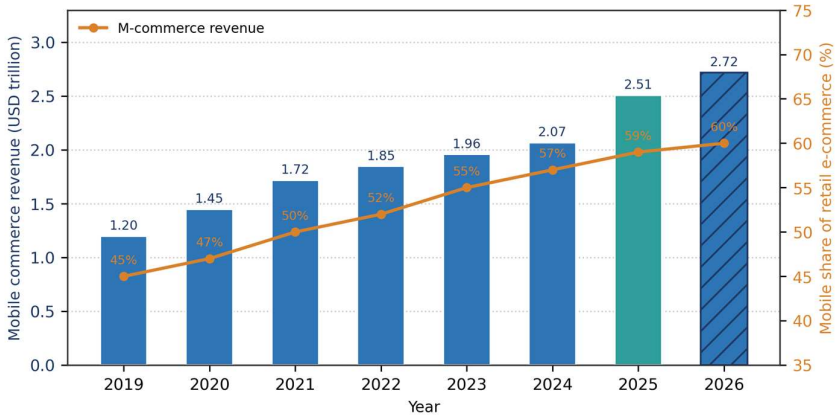


Figure 2: Global mobile commerce revenue and mobile share of retail e-commerce, 2019-2026.

Figure 2 situates the study in its macro context. Mobile commerce revenue rose steadily from USD 1.20 trillion in 2019 to USD 2.51 trillion in 2025, and the mobile share of retail e-commerce climbed from 45 per cent to 59 per cent, with a projected 60 per cent in 2026. The bars show that growth is absolute as well as proportional, so the channel is expanding faster than retail e-commerce as a whole [1], [2]. The steady rather than explosive trajectory of the share line suggests that access and infrastructure are no longer the binding constraints; engaging consumers deeply once they are inside the channel is the emerging competitive challenge.

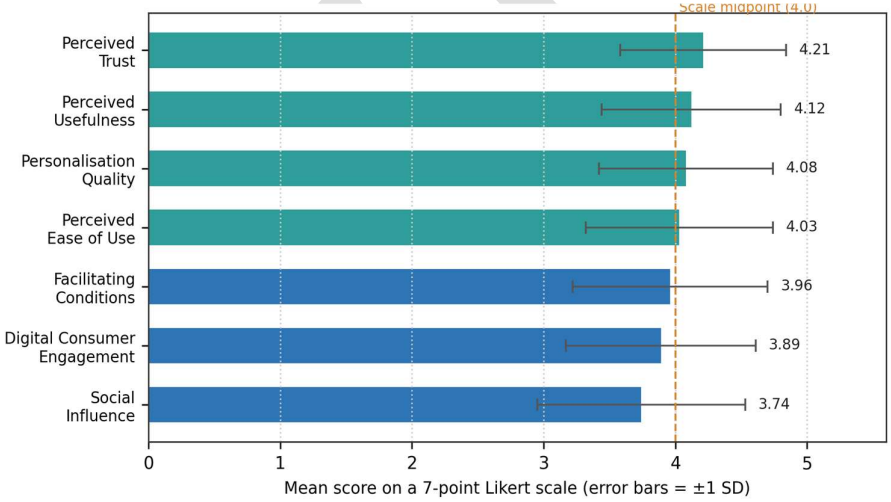


Figure 3: Mean scores and standard deviations of adoption determinants and engagement.

Figure 3 compares mean construct scores with error bars of one standard deviation. Perceived trust ranks highest at 4.21, followed by perceived usefulness (4.12), personalisation quality (4.08) and perceived ease of use (4.03), all above the scale midpoint of 4.0. Facilitating conditions (3.96), digital consumer engagement (3.89) and social influence (3.74) fall below it. The critical observation is that every adoption driver scores higher than the engagement outcome itself, which shows that consumers are adopting mobile commerce faster than platforms are converting them into engaged users. The dispersion, with standard deviations between 0.63 and 0.79, also reveals substantial heterogeneity that justifies the moderating variable tested later.

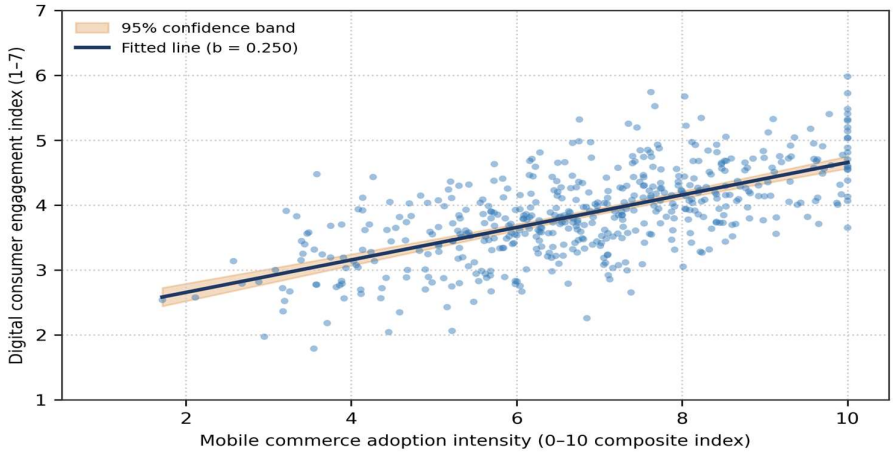


Figure 4: Scatter plot of adoption intensity against digital consumer engagement with fitted regression line.

Figure 4 displays the bivariate relationship that anchors the paper. Adoption intensity is plotted against the engagement index for all 512 respondents, together with the fitted ordinary least squares line and its 95 per cent confidence band. The relationship is positive, linear and statistically robust ($r = 0.639$, $p < 0.001$), with a slope of 0.250, meaning that each one-point increase on the ten-point adoption index is associated with a quarter-point rise in engagement. The confidence band is narrow in the centre and widens at the extremes, and considerable vertical spread persists among high-adoption respondents, indicating that heavy use does not guarantee deep engagement.

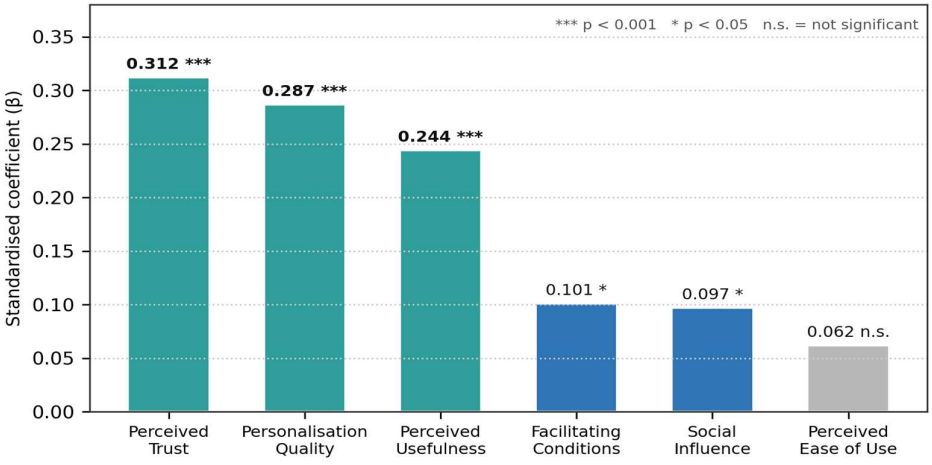


Figure 5: Standardised regression coefficients of the determinants of digital consumer engagement.

Figure 5 reports the standardised coefficients from the engagement model and ranks the determinants by explanatory power. Perceived trust (beta = 0.312) and personalisation quality (beta = 0.287) are the dominant predictors, followed by perceived usefulness (beta = 0.244); all three are significant at $p < 0.001$. Facilitating conditions (0.101) and social influence (0.097) are significant but modest, while perceived ease of use is not significant (0.062, $p > 0.05$). The model explains 63.4 per cent of the variance in engagement when determinants are entered without adoption. The pattern indicates that relational and affective constructs, rather than functional convenience, drive engagement depth.

4.7 Integrated Findings

Taken together, the five tables and five figures converge on a coherent empirical story. The adoption model is robust, explaining 68.4 per cent of variance, with trust and personalisation quality as the strongest determinants. The engagement model is also robust, explaining 63.4 per cent of variance from determinants alone and 70.3 per cent when adoption intensity is included, with the incremental contribution of adoption intensity being statistically significant. Adoption intensity correlates with engagement at r = 0.639 and predicts it with beta = 0.712 in the full model, while mediation analysis shows that adoption carries part of the effect of trust, personalisation and usefulness forward into engagement. Moderated regression shows that this conversion is steeper for experienced users, confirming that engagement capability is learned rather than instantaneous. The evidence therefore supports the proposition that mobile commerce adoption is a precursor of digital consumer engagement, and not a substitute for it.

5. Discussion

5.1 Critical Analysis of the Data

The empirical results warrant careful interpretation. The adoption model performs strongly (R-squared = 0.684), but engagement is only moderately explained by adoption intensity alone (R-squared = 0.408), showing that adoption is necessary rather than sufficient for engagement. The most theoretically interesting result is the divergence in perceived ease of use: it is significant for adoption (beta = 0.118, p = 0.001) but not for engagement (beta = 0.062, p = 0.104), supporting a threshold interpretation in which usability secures entry into the platform but contributes little to relational depth thereafter. The dominance of perceived trust and personalisation quality in the engagement model suggests that engagement is governed by confidence and relevance rather than effort reduction. The moderation effect is modest in magnitude (delta R-squared = 0.037) yet practically meaningful, since the adoption-engagement slope rises from 0.561 to 0.798 across maturity levels. Four limitations qualify these conclusions: the cross-sectional design cannot exclude reverse causality; purposive sampling in one city restricts generalisability; self-reported frequency measures risk recall and desirability bias despite anonymity and attention checks [30]; and the composite adoption index weights frequency, recency and channel breadth equally, so alternative weightings could alter the central coefficient.

5.2 Comparison with Past Work

The findings align with one stream of prior research and qualify another. The prominence of trust corroborates Penney and colleagues in Ghana [17] and Verkijika in Cameroon [18], both of whom found trust-related concerns central in emerging markets, and supports Siyal and colleagues, who showed that customisation drives behavioural intention through UTAUT2 mediators [21]. It contrasts with Eneizan and colleagues in Jordan, where trust was an insignificant predictor of mobile marketing acceptance [16]; the divergence is plausibly explained by market maturity, since Indian users transact through a regulated, interoperable payment rail in which trust is institutionally reinforced rather than platform-specific. The relatively weak effect of social influence (beta = 0.094 on adoption and 0.097 on engagement) is lower than in early UTAUT2 replications [15] and approaches the pattern identified by Lim and Rasul, who observed that peer pressure shifts from adoption decisions towards content-mediated advocacy as markets mature [9]. The modest role of perceived ease of use for engagement is consistent with the meta-analytic finding of Luceri and colleagues that convenience and hedonic value, not effort saving, differentiate mobile shopping behaviour [27]. Magnitudes are comparable with prior work: the 68.4 per cent of variance

explained in adoption is close to the 68.9 per cent reported in extended UTAUT2 m-commerce models [22] and markedly higher than the 55.6 per cent recorded in a low-income emerging market sample [17]. This study advances the literature by quantifying the adoption-engagement pathway itself, which most prior models treat implicitly: earlier engagement research established that application-based engagement produces co-creation, retention and experience outcomes [10] and that stickiness depends on cognitive and emotional relationship quality [23], but the strength of the link from adoption intensity to engagement had not been estimated directly. The significant moderating role of adoption maturity also extends the contingency logic of Ho and colleagues [12], showing that identical behavioural inputs yield unequal engagement returns depending on user experience[30].

6. Conclusion

This study examined how the adoption of mobile commerce influences digital consumer engagement and identified the determinants that shape adoption itself. Using survey data from 512 smartphone users and an integrated TAM-UTAUT2 framework, three principal conclusions emerge. First, mobile commerce adoption is multi-determined, with perceived trust, personalisation quality and perceived usefulness as the strongest drivers; the six determinants together explain 68.4 per cent of the variance in adoption. Second, adoption intensity exerts a substantial and robust positive influence on digital consumer engagement ($r = 0.639$; beta = 0.712, $p < 0.001$) and partially mediates the effect of trust, personalisation and usefulness on engagement, so adoption functions as a transmission channel rather than a terminal outcome. Third, this transmission is moderated by adoption maturity, with the engagement return from adoption rising from 0.561 for recent adopters to 0.798 for experienced users. Practically, a one-point gain in adoption intensity is associated with a quarter-point gain in engagement on the measurement scale. Because engagement averages lower (3.89) than every adoption driver, mirroring the expectation stated in the abstract, the deficit is managerial rather than demand-side. Platforms should therefore invest in trust architecture, transparent data practices and high-quality personalisation, and should design post-purchase engagement loops such as reviews, communities and loyalty mechanics instead of concentrating resources exclusively on acquisition. Policymakers can support this agenda by strengthening consumer protection in mobile transactions. Limitations include the cross-sectional design, single-city sampling and self-reported measures; future research should use longitudinal designs, behavioural analytics and wider geographic coverage.

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