DOI: https://doi.org/10.71317/kjard.2.10.2026.811

Kashmir Journal of Academic Research and Development

Journal homepage: https://rjsaonline.org/index.php/KJARD

Technology Acceptance and Online Purchase Intention among Pakistani Consumers: The Roles of Attitude and Internet Literacy

Yasir Aftab Farooqi
Assistant Professor, Faculty of Management and Administration Sciences (FMAS), University of Gujrat, Pakistan
Email: yasir.aftab@uog.edu.pk
Rehan Ali
BBA Graduate, Faculty of Management Sciences, UCP Constituent Campus, Gujrat, Pakistan
Email: rehanalich005@gmail.com
Umar Azmat
BBA Graduate, Faculty of Management Sciences, UCP Constituent Campus, Gujrat, Pakistan
Email: umarch0008@gmail.com
Waqas Manzoor
Assistant Professor, Faculty of Management and Administration Sciences (FMAS), University of Gujrat, Pakistan
Email: waqas.manzoor@uog.edu.pk
Sheraz Anjum
PhD Scholar, Faculty of Business and Management, Universiti Sultan Zainal Abidin, Terengganu, Malaysia
Email: sheraz153@hotmail.com
Farwa Bugvi
PhD Scholar, Superior University, Lahore, Pakistan
Email: farwabugvi2013@gmail.com

ARTICLE INFO

Received:
August 31, 2026
Revised:
September 13, 2026
Accepted:
September 30, 2026
Available Online:
October 11, 2026

Keywords:
Technology Acceptance Model; perceived usefulness; perceived ease of use; attitude; internet literacy; online purchase intention; PLS-SEM; Pakistan

Corresponding Author:
Yasir Aftab Farooqi
Email: yasir.aftab@uog.edu.pk

ABSTRACT

Connectivity in Pakistan has expanded rapidly, yet it remains unclear which technology perceptions and consumer competencies turn favourable evaluations of online shopping into purchase intention. Drawing on the Technology Acceptance Model (TAM), this study tests an integrated model in which perceived usefulness (PU) and perceived ease of use (PEOU) influence online purchase intention (OPI) directly and indirectly through attitude toward online shopping (AT), and in which internet literacy (IL) conditions the attitude–intention link. Survey data from 240 Pakistani online shoppers were analysed with partial least squares structural equation modelling (SmartPLS 4; 5,000 bias-corrected and accelerated bootstrap resamples). The measurement model showed high reliability, convergent validity, and discriminant validity (HTMT ≤ .78), and neither Harman's test (40.3% of variance) nor full-collinearity diagnostics (VIF ≤ 3.27) indicated serious common method bias. PU (β = .706) and PEOU (β = .412) predicted AT. AT (β = .354), PU (β = .326), and PEOU (β = .198) predicted OPI, and AT partially mediated the effects of PU (indirect β = .250) and PEOU (indirect β = .146). IL had a strong direct effect on OPI (β = .441) and positively moderated the AT–OPI relationship (β = .106, $p < .001$): the effect of attitude was .460 at high and .248 at low literacy. The model explained 69.1% of the variance in AT and 74.1% in OPI. The findings extend TAM by showing that attitude converts into intention more strongly among digitally skilled consumers, and they imply that usability improvements should be paired with digital-skills support.

Introduction

Online retail is one of the main modalities by which consumers in emerging economies discover, assess and purchase products online, but digital connectivity is not necessarily a prerequisite for commercialization. This is the paradox that is illustrated by Pakistan. In early 2025, the country had approximately 116 million internet users and over 190 million mobile connections (Kemp, 2025), and consumers remain wary of issues of payment security, product authenticity and delivery reliability when evaluating whether or not to shop online (Saleem et al., 2022; Saoula et al., 2023). Knowing the reason of positive attitudes towards online shopping and how they fail to convert into buying intentions becomes theoretical and practical priority for the Pakistani digital economy.

The technology acceptance model (TAM; Davis, 1989; Davis et al., 1989) is still the most popular framework for understanding consumer technology-related behaviour. TAM is based on theory of reasoned action (Fishbein & Ajzen, 1975) which suggests that PU and PEOU influence users' attitudes and intentions. The original model has been extended multiple times (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2012) and adapted to online shopping by incorporating some factors such as trust, risk and shopping motivations (Childers et al., 2001; Gefen et al., 2003; Pavlou, 2003). Meta-analyses show its robustness across settings (King & He, 2006; Schepers & Wetzels, 2007). There are two outstanding questions, however. For one, the original tests (Davis et al., 1989) had a partial mediation of attitude; as a result, later versions of this test (e.g., Venkatesh & Davis, 2000) excluded attitude; however, in the field of consumer research, where evaluative judgements are relevant, attitude remains a factor of explanation (e.g., Childers et al., 2001; Saleem et al., 2022). Secondly, TAM provides little information on the capabilities that consumers must have to convert their intentions into action. This is particularly notable, however, in the context of the well-documented intention–behaviour gap (Sheeran & Webb, 2016), and the fact that inequalities in internet skills persist despite high levels of access (Hargittai, 2002; van Deursen & van Dijk, 2019).

Research on Pakistani consumers has examined TAM-based drivers of online purchase intention (Bhatti et al., 2022; Saleem et al., 2022) and boundary conditions such as brand awareness, perceived risk, and web atmospherics (Majeed et al., 2024). Evidence on digital literacy, by contrast, treats it either as a direct antecedent of purchase intention (Nazzal et al., 2021) or as a moderator of the satisfaction–continuance link (Restianto et al., 2024). We are not aware of a study that tests, within one model, whether internet literacy conditions the attitude–intention relationship while attitude simultaneously mediates the effects of PU and PEOU among Pakistani online shoppers.

This study addresses that gap through four research objectives: (RO1) to estimate the direct effects of PU and PEOU on attitude toward online shopping (AT) and on online purchase intention (OPI); (RO2) to test the effect of AT on OPI; (RO3) to determine whether AT mediates the effects of PU and PEOU on OPI; and (RO4) to test whether internet literacy (IL) moderates the AT–OPI relationship. The study contributes in three ways. Theoretically, it retains attitude as an explicit mechanism in TAM and positions internet literacy as a boundary condition that links TAM to the theory of planned behaviour (Ajzen, 1991). Empirically, it provides evidence from an under-researched emerging-market setting using current PLS-SEM reporting standards (Hair et al., 2019; Sarstedt et al., 2022). Practically, it indicates whether e-commerce operators should prioritise usefulness, usability, attitude building, or skills support.

Literature Review and Hypothesis Development

Theoretical Background and Constructs

According to Davis (1989), perceived usefulness is defined as the extent to which the person finds that use of the system would be useful to them and perceived ease of use is the extent to which the person believes it will be easy to use. As specified in the original, both beliefs affect attitude, and attitude predicts intention directly, while usefulness affects intention directly, too (Davis et al., 1989). This is similar to the theory of reasoned action, which proposed that attitude is a proximal predictor of intention (Fishbein & Ajzen, 1975), and the theory of planned behaviour, which added perceived behavioural control, reflecting skills and resources, as another determinant of intention and action (Ajzen, 1991, 2020).

For online shopping, beliefs regarding the time and money saved for online shopping (PU) and increased product choice (PEOU) are measured. Attitude is consumers' overall positive or negative rating of online shopping, and OPI is the consumer's perceived probability of purchasing online (Pavlou, 2003). Internet literacy refers to the ability to find and evaluate information, transact, and protect personal data online, and it spans operational, cognitive, and socio-emotional skills (Eshet-Alkalai, 2004; Ng, 2012). Here it is operationalised as self-assessed proficiency, which makes it conceptually close to computer self-efficacy (Compeau & Higgins, 1995) and perceived behavioural control.

Hypotheses

Technology perceptions and attitude (H1, H3)

TAM holds that beliefs about usefulness and ease of use form attitudes. When shopping online is seen as productive, economical, and cognitively undemanding, consumers evaluate it more favourably (Childers et al., 2001; Davis et al., 1989). Studies of Pakistani consumers report that TAM beliefs shape attitudes toward online purchasing (Saleem et al., 2022). We therefore propose:

- *H1*. PU has a positive effect on AT.
- *H3*. PEOU has a positive effect on AT.

Direct effects on intention (H2, H4, H5)

Beyond their effects through attitude, PU and PEOU may influence intention directly. Davis et al. (1989) found that usefulness affected intention independently of attitude, because people may intend to use an instrumental technology regardless of how they feel about it. Ease of use may likewise reduce the anticipated effort and risk of failed transactions. Empirical results on PEOU are mixed: PU but not PEOU predicted online purchase intention among Palestinian internet users (Nazzal et al., 2021), and meta-analytic evidence shows PU to be generally the stronger predictor (King & He, 2006). Given this inconsistency, both direct paths are retained. Attitude is expected to predict intention because, under the theories of reasoned action and planned behaviour, evaluations are proximal determinants of intention (Ajzen, 1991; Fishbein & Ajzen, 1975). Attitudes based on direct experience are especially predictive of later behaviour (Glasman & Albarracín, 2006), which suits a sample of consumers with prior online-shopping exposure.

- *H2*. PU has a positive effect on OPI.
- *H4*. PEOU has a positive effect on OPI.
- *H5*. AT has a positive effect on OPI.

Mediating role of attitude (H6, H7)

If PU and PEOU shape attitude (H1, H3) and attitude shapes intention (H5), attitude should transmit part of their influence to OPI. Saleem et al. (2022) reported such a mediating role of attitude among Pakistani consumers. Because PU and PEOU may also act directly (H2, H4), partial rather than full mediation is anticipated.

- *H6*. AT mediates the relationship between PU and OPI.
- *H7*. AT mediates the relationship between PEOU and OPI.

Internet literacy as a boundary condition (H8)

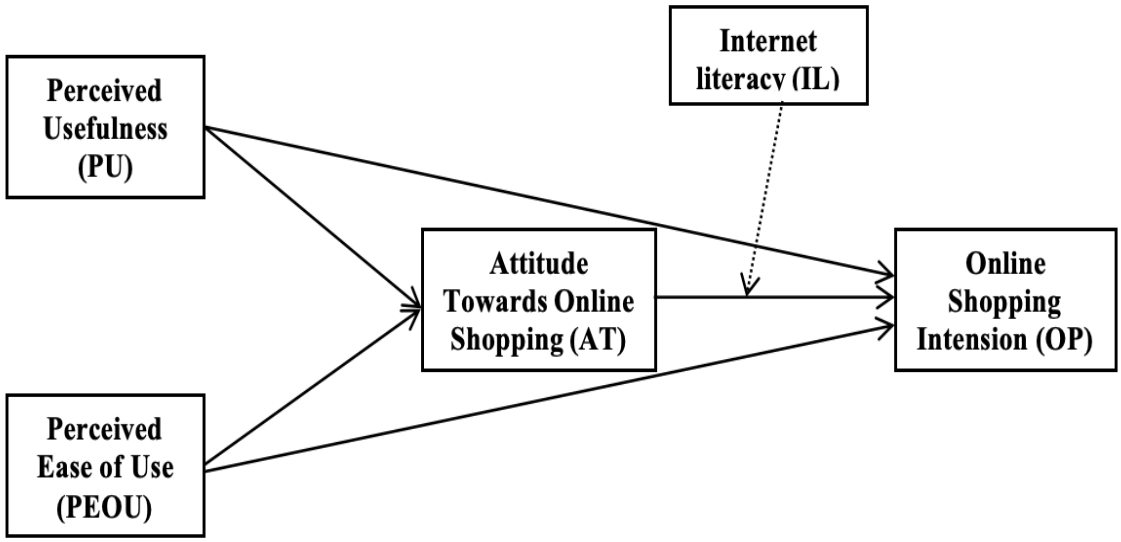
Attitude–intention consistency is not automatic. Even a favourable evaluation requires the competence to search for products, judge seller credibility, use digital payments, and protect personal data. According to the theory of planned behaviour, people are more likely to form and act on intentions when they feel capable of performing the behaviour (Ajzen, 1991; Compeau & Higgins, 1995), and differences in online skills constitute a second-level digital divide that shapes what people do online (Hargittai, 2002; Hargittai & Hsieh, 2012; van Deursen & van Dijk, 2019). Digital literacy has been associated with online purchase intention (Nazzal et al., 2021) and has been found to strengthen the link between user satisfaction and continued use of e-commerce (Restianto et al., 2024). Skilled consumers can therefore translate a favourable attitude into a concrete purchase plan, whereas less-skilled consumers with similar attitudes may remain hesitant because they anticipate difficulty or risk.

- *H8*. IL positively moderates the effect of AT on OPI, such that the effect is stronger at higher levels of IL.

Conceptual Model

Figure 1 summarises the model. IL is also specified as a direct predictor of OPI so that the interaction is estimated net of the moderator's main effect (Memon et al., 2019); this path is a control rather than a hypothesis.

Figure 1: ***Conceptual Model and Hypotheses***



Note. PU = perceived usefulness; PEOU = perceived ease of use; AT = attitude toward online shopping; OPI = online purchase intention. The dashed line is the control path from internet literacy to OPI.

Method

Research Design

A cross-sectional, quantitative survey design was used to test the hypotheses deductively. Data were analysed with partial least squares structural equation modelling (PLS-SEM), which is well suited to prediction-oriented models that combine mediation and moderation and include several reflective latent constructs (Hair et al., 2019; Sarstedt et al., 2022; Shiau et al., 2019).

Population, Sampling, and Sample Size

The target population comprised Pakistani residents aged 18 years or older with at least some experience of browsing or purchasing through an e-commerce website or mobile application, because respondents need such exposure to judge usefulness, ease of use, and attitude. There was no sampling frame of the online shoppers available, therefore, non-probability convenience sampling using purposive screening was employed as is common in consumer research in emerging markets as cited by Etikan et al. (2016) and Hair et al. (2022). A question paper was circulated online via social media, University networks and online-shopping forums. A total of N = 240 cases remained after discarding incomplete and straight-lined answers.

Sample size was assessed using GPower 3.1 (Faul et al., 2009). If the regression is the most complex in the model (OPI, 5 predictors including the interaction term), then, for a medium effect (f^2 = .15), n = 55 and, for a small-to-medium effect (f^2 = .05), n = 159. The inverse square root method (Kock & Hadaya, 2018) suggests that, at 80% power, a path coefficient of approximately .16 or greater can be detected by N = 240 and that power to detect an interaction of f^{*2} = .05 is .93. The sample thus exceeds these requirements.

Instrument and Measures

The questionnaire consisted of two parts. The demographic data and a screening item about previous online shopping experience were gathered in Section A. 24 reflective items with five-point Likert scales (1 = strongly disagree to 5 = strongly agree) were used to measure the five constructs in Section B. Selected items were created based on existing scales from TAM and online-shopping and were adapted for the context of e-commerce in Pakistan (Table 1) and are fully worded in Appendix A.

Table 1: Measurement Sources and Item Allocation

Construct	Items	Source
Perceived usefulness (PU)	6	Adapted from Davis (1989); Bhatti et al. (2022)
Perceived ease of use (PEOU)	6	Adapted from Davis (1989); Saleem et al. (2022)

Construct	Items	Source
Attitude toward online shopping (AT)	4	Adapted from Fishbein & Ajzen (1975); Bhatti et al. (2022)
Online purchase intention (OPI)	3	Adapted from Bhatti et al. (2022); Majeed et al. (2024)
Internet literacy (IL)	5	Developed for this study, informed by Eshet-Alkalai (2004) and Ng (2012)
Total	**24**	

Note. All items used five-point Likert scales.

The item clarity and wording were evaluated with a small sub-sample in a pilot test, with minor wording changes; especially in IL, proficiency was not confused with access. Common method bias was addressed by using the following procedure (Podsakoff et al., 2012, 2024): The use of respondent anonymity was assured by the respondents, predictor and criterion items were separated in the questionnaire flow, and the cover message stated there were no right or wrong answers. Participants were encouraged to participate anonymously and voluntarily, informed consent was given prior to data entry, no identifying information was gathered, and the participants were able to opt out before submitting.

Data Analysis

The analyses were performed with SmartPLS 4 (Ringle et al., 2024) under the path weighting scheme with the maximum number of iterations set at 3,000 and the stop criterion at 10^{-7}. The standard errors, t values and the confidence intervals were from the 2-tailed bootstrap with 5000 subsamples, with the bias-corrected and accelerated (BCa) 95% intervals (Streukens & Leroi-Werelds, 2016). The data for the indicators were used in computation of descriptive statistics, Harman's single-factor test and item-level checks.

The measurement model was assessed using the current guidelines (Hair et al., 2019; 2020; 2022). The outer loadings of the indicators had to be .708 or better for reliability. Internal consistency was examined using the Cronbach's α, ρa and composite reliability (ρc) ranging from .70 to .95, which is considered satisfactory as values of .95 and above suggest item redundancy (Drolet & Morrison, 2001; Hair et al., 2019). Convergent validity required an average variance extracted (AVE) above .50. Discriminant validity was assessed with the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the heterotrait–monotrait ratio (HTMT), with values below .85 indicating adequate distinctiveness (Henseler et al., 2015). Common method bias was examined with Harman's single-factor test (Podsakoff et al., 2003) and with a full-collinearity assessment, for which variance inflation factors (VIFs) at or below 3.3 indicate that the model is free of pervasive method bias (Kock, 2015; Kock & Lynn, 2012). Because Harman's test has limited sensitivity, it was used only in combination with the VIF criterion (Fuller et al., 2016).

The structural model was evaluated through inner-model VIFs, path coefficients, coefficients of determination (R^2), effect sizes (f^2; .02 small, .15 medium, .35 large; Cohen, 1988), and model fit indices (SRMR, *d*ULS, *d*G; Henseler et al., 2016). Mediation was tested with bootstrapped specific indirect effects and classified by comparing direct and indirect effects (Nitzl et al., 2016; Zhao et al., 2010). Moderation was tested with the two-stage approach, in which the product of the latent variable scores of AT and IL forms the interaction term (Henseler & Chin, 2010). The interaction was interpreted through simple slopes at the mean and ±1 *SD* of IL (Memon et al., 2019).

Results

Respondent Profile

Table 2 summarises the respondents. The sample was predominantly female (83.0%) and young (82.0% aged 18–24; 16.0% aged 25–30), and highly educated (85.0% held a bachelor's or master's degree). Most respondents lived in Islamabad (55.0%) or Gujrat (36.5%), 57.0% reported a household income in the PKR 300,000 bracket, 71.5% shopped online "sometimes" and 13.5% "often", and 92.5% used a smartphone.

Table 2: Respondent Demographic Profile

Characteristic	Category	%
Gender	Male	17.0
	Female	83.0
Age (years)	18–24	82.0
	25–30	16.0
	31–40	1.5

Characteristic	Category	%
	41–60	0.5
Qualification	Matric	3.0
	Intermediate	12.0
	Bachelor's degree	31.0
	Master's degree	54.0
Monthly household income (PKR)	~30,000	17.5
	~100,000	21.0
	~300,000	57.0
	~500,000	4.5
City	Islamabad	55.0
	Gujrat	36.5
	Lahore	2.0
	Other	6.5
Online shopping frequency	Sometimes	71.5
	Often	13.5
	Occasionally	11.0
	Never	4.0
Preferred platform	Alibaba	51.0
	Social media	27.0
	Daraz	8.5
	Other	13.5
Device used	Smartphone	92.5
	Tablet	3.0
	Other	2.5
	Laptop	2.0

Note. Percentages are within each characteristic and may not sum to 100 because of rounding. Respondents confirmed prior experience of browsing or purchasing online at screening. Income brackets are approximate coded values. sample size (N = 240).

Data Screening and Common Method Bias

There were no missing values in the 240 cases that were retained. The ranges of skewness and excess kurtosis (|skew| ≤ 0.22 and |kurtosis| ≤ 0.77, respectively) were within accepted limits (Kline, 2023; Appendix A, Table A1). The results of Harman's single factor test were found that the first unrotated factor explained 40.3% of the total variance in the 24 items, which was lower than the 50% criterion (Podsakoff et al., 2003); the second and third factors accounted for 21.4% and 18.3% of the total variance, respectively, indicating a multidimensional structure. All inner-model VIFs were between 1.00 and 3.27, which is below the 3.3 criteria (Kock, 2015) in the full-collinearity assessment. When taken together, these checks show that common method bias is not a pervasive concern, but cannot be entirely ruled out by a single-source survey (see Section 5.4).

Measurement Model

Table 3 reports the measurement model. All 24 outer loadings exceeded .708 (range = .886–.945) and were significant ($p < .001$, all $t > 55$; Table A1). Cronbach's α (.905–.969), ρa (.905–.969), and ρc (.940–.975) exceeded .70, and AVE values (.803–.871) exceeded .50, supporting reliability and convergent validity. Composite reliability for PU, PEOU, and IL (ρc = .971–.975) and most loadings above .90 are, however, higher than the .95 level at which item redundancy becomes a concern (Drolet & Morrison, 2001; Hair et al., 2019). All items were retained because they cover distinct aspects of their constructs and because discriminant validity was unaffected; this issue is revisited in Section 5.4.

Table 3: Reliability and Convergent Validity of the Measurement Model

Construct	*k*	*M*	*SD*	Loadings	α	ρ*a*	ρ*c*	AVE
Perceived usefulness	6	3.43	0.82	.921–.942	.969	.969	.975	.866
Perceived ease of use	6	3.37	0.75	.908–.937	.965	.967	.971	.849
Attitude toward online shopping	4	3.23	0.58	.886–.907	.918	.918	.942	.803
Online purchase intention	3	4.13	0.60	.910–.925	.905	.905	.940	.840
Internet literacy	5	3.49	0.81	.927–.945	.963	.967	.971	.871

Note. *k* = number of items; *M* and *SD* are for item-average scores (1–5 scale); α = Cronbach's alpha; ρ*a* = reliability coefficient rho-A; ρ*c* = composite reliability; AVE = average variance extracted. *N* = 240.

Discriminant Validity

Table 4 shows that the square root of each construct's AVE exceeded its correlations with all other constructs, satisfying the Fornell–Larcker criterion. The highest HTMT ratio was .778 (AT–OPI), below the .85 threshold, and the upper limits of all BCa 95% intervals were at most .842 (Henseler et al., 2015). The five constructs are therefore empirically distinct. PU and PEOU were almost uncorrelated (r = .04) and neither was related to IL (r = .02 and .10), which is discussed in Section 5.1.

Table 4: Discriminant Validity: Fornell–Larcker Criterion and HTMT

Construct	1	2	3	4	5
1. Perceived usefulness	.930	.048	.766	.629	.038
2. Perceived ease of use	.040	.922	.466	.420	.096
3. Attitude toward online shopping	.723	.440	.896	.778	.102
4. Online purchase intention	.589	.394	.709	.917	.528
5. Internet literacy	.016	.095	.098	.495	.933

Note. Diagonal values are the square roots of AVE; values below the diagonal are latent variable correlations (Fornell–Larcker); values above the diagonal are HTMT ratios. All HTMT values are below .85.

Structural Model and Direct Effects

Inner-model VIFs were between 1.00 and 3.27 (Table 5), indicating no critical collinearity; the highest value (AT → OPI, 3.27) lay just below the 3.3 cut-off and under the more lenient limit of 5. The model explained 69.1% of the variance in AT (adjusted R^2 = .689) and 74.1% in OPI (adjusted R^2 = .736), which are moderate to substantial levels (Hair et al., 2011). Model fit was satisfactory: for the estimated model, SRMR = .034 (HI95 = .036), dULS = .341 (HI95 = .381), and dG = .278 (HI95 = .346), with all values below their 95% bootstrap quantiles and SRMR below .08 (Henseler et al., 2016).

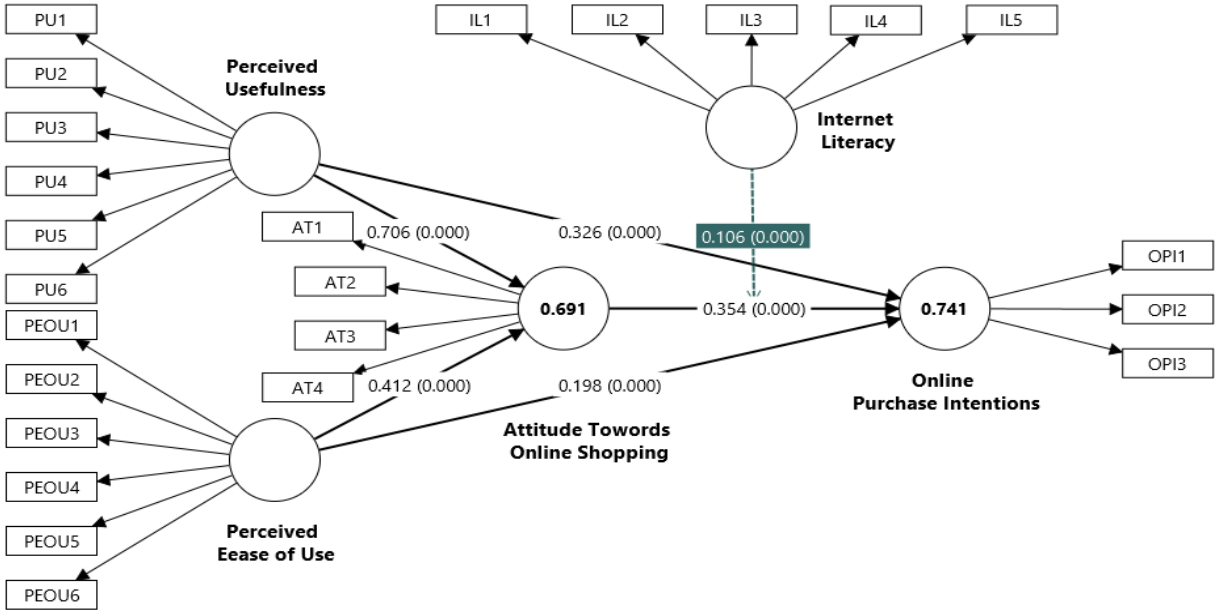
Table 5 and Figure 2 present the path estimates. PU (β = .706, t = 22.30, p < .001) and PEOU (β = .412, t = 10.37, p < .001) had significant positive effects on AT, supporting H1 and H3. PU (β = .326, t = 5.54, p < .001), PEOU (β = .198, t = 4.39, p < .001), and AT (β = .354, t = 5.31, p < .001) had significant positive effects on OPI, supporting H2, H4, and H5. The effect of PU on AT was very large (f^2 = 1.61) and that of PEOU on AT large (f^2 = 0.55); effects on OPI were small to medium (f^2 = 0.10–0.16). Internet literacy, included as a control path, had a strong direct effect on OPI (β = .441, t = 11.73, p < .001; f^2 = 0.74).

Table 5: Structural Model: Path Coefficients and Hypothesis Tests

Path	β	*SD*	*t*	*p*	95% BCa CI	f^2	VIF	Decision
H1: PU → AT	.706	.032	22.30	<.001	[.639, .764]	1.61	1.00	Supported
H2: PU → OPI	.326	.059	5.54	<.001	[.210, .439]	0.16	2.63	Supported
H3: PEOU → AT	.412	.040	10.37	<.001	[.331, .487]	0.55	1.00	Supported
H4: PEOU → OPI	.198	.045	4.39	<.001	[.107, .283]	0.10	1.57	Supported
H5: AT → OPI	.354	.067	5.31	<.001	[.224, .484]	0.15	3.27	Supported
H8: IL × AT → OPI	.106	.030	3.55	<.001	[.053, .167]	0.05	1.02	Supported

Note. β = standardised path coefficient; *SD* = bootstrap standard deviation; BCa CI = bias-corrected and accelerated 95% confidence interval (5,000 subsamples, two-tailed). PU = perceived usefulness; PEOU = perceived ease of use; AT = attitude toward online shopping; OPI = online purchase intention; IL = internet literacy. R^2 = .691 (AT) and .741 (OPI). *N* = 240.

Figure 2: Structural Model With Standardised Path Coefficients



Note. Coefficients are standardised path estimates from the bootstrapped model (*N* = 240). The dashed line is the control path from internet literacy to OPI. ** p* < .001.

Mediation Analysis

Table 6 shows that the specific indirect effects of PU (β = .250, *t* = 5.21, 95% BCa CI [.158, .346]) and of PEOU (β = .146, *t* = 4.52, 95% BCa CI [.086, .215]) on OPI through AT were significant, supporting H6 and H7. Because the direct effects of PU and PEOU on OPI were also significant and had the same sign as the indirect effects, AT acts as a complementary partial mediator for both relationships (Nitzl et al., 2016; Zhao et al., 2010). The indirect paths accounted for 43.4% (PU) and 42.4% (PEOU) of the total effects.

Table 6: Specific Indirect and Total Effects on Online Purchase Intention

Effect	β	*SD*	*t*	*p*	95% BCa CI	Result
Specific indirect effects						
H6: PU → AT → OPI	.250	.048	5.21	<.001	[.158, .346]	Supported; partial (VAF = 43.4%)
H7: PEOU → AT → OPI	.146	.032	4.52	<.001	[.086, .215]	Supported; partial (VAF = 42.4%)
Total effects						
PU → OPI	.576	.037	15.56	<.001	[.500, .646]	
PEOU → OPI	.344	.039	8.72	<.001	[.265, .419]	

Note. VAF = variance accounted for (indirect effect ÷ total effect). Direct effects are reported in Table 5. *N* = 240.

Moderation Analysis

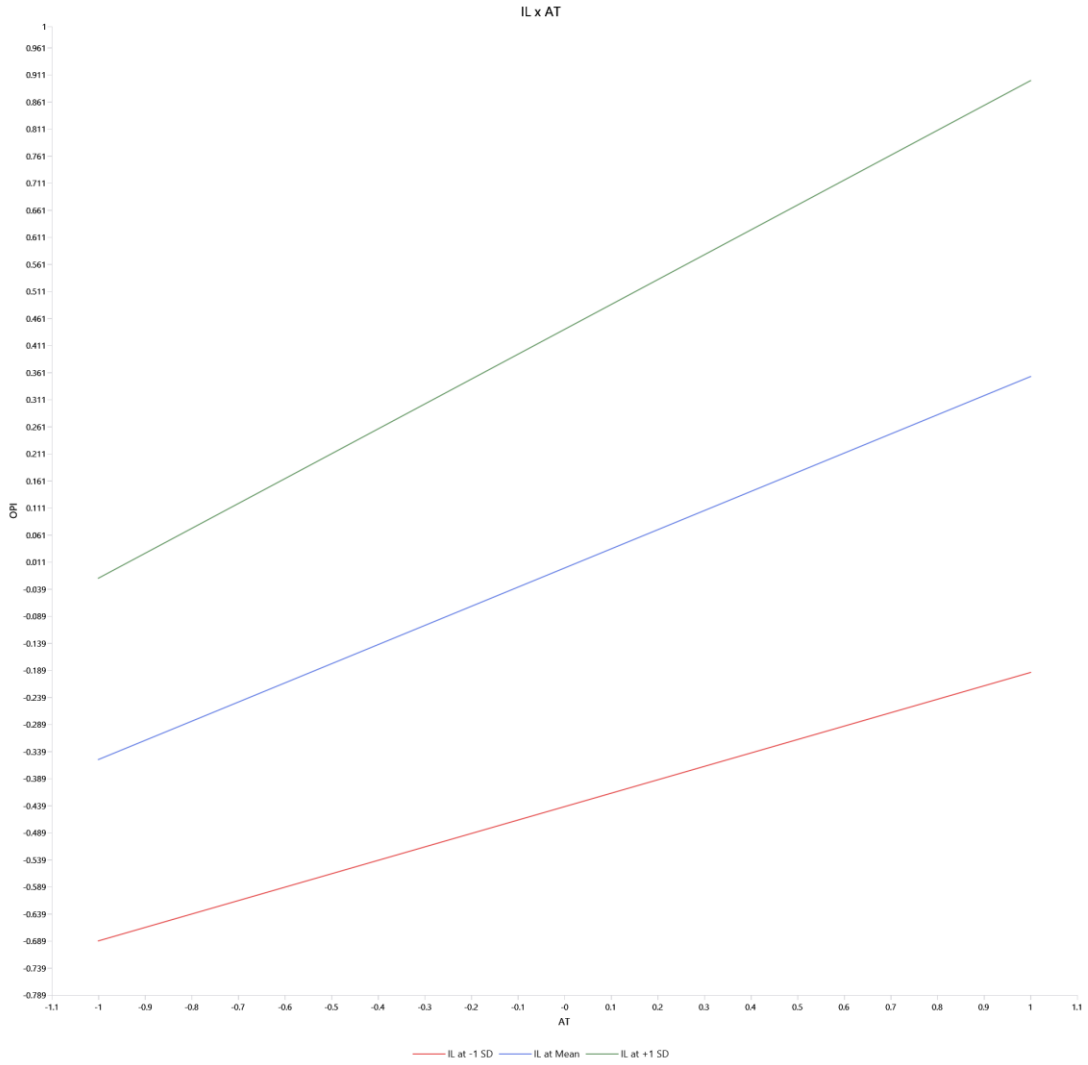
The AT × IL interaction had a significant positive effect on OPI (β = .106, *t* = 3.55, *p* < .001, 95% BCa CI [.053, .167]), supporting H8. The interaction was small in effect size (f^2 = 0.049) and increased the explained variance of OPI by roughly 1.3 percentage points, which is typical of interaction effects in field research (Aguinis et al., 2005; Chin et al., 2003). The simple-slope analysis in Table 7 and Figure 3 shows that the AT–OPI effect was .248 at low IL (−1 *SD*), .354 at mean IL, and .460 at high IL (+1 *SD*); all three slopes were significant, but the effect of attitude at high literacy was almost twice that at low literacy. Conditional indirect effects of PU and PEOU through AT showed the same ascending pattern.

Table 7: Conditional Effects of Attitude and Indirect Effects at Levels of Internet Literacy

Effect	β	*SD*	*t*	*p*	95% BCa CI	Level of IL
Conditional direct effect: AT → OPI						
Low IL	.248	.078	3.18	.001	[.091, .394]	−1 *SD*
Mean IL	.354	.067	5.31	<.001	[.224, .484]	Mean
High IL	.460	.068	6.79	<.001	[.328, .591]	+1 *SD*
Conditional indirect effect: PU → AT → OPI						
Low IL	.175	.056	3.14	.002	[.064, .283]	−1 *SD*
Mean IL	.250	.048	5.21	<.001	[.158, .346]	Mean
High IL	.325	.049	6.68	<.001	[.234, .422]	+1 *SD*
Conditional indirect effect: PEOU → AT → OPI						
Low IL	.102	.034	2.97	.003	[.037, .172]	−1 *SD*
Mean IL	.146	.032	4.52	<.001	[.086, .215]	Mean
High IL	.189	.035	5.38	<.001	[.125, .265]	+1 *SD*

Note. IL = internet literacy; AT = attitude toward online shopping; OPI = online purchase intention. Conditional indirect effects are descriptive; no formal index of moderated mediation was estimated. N = 240.

Figure 3: Simple Slopes of the Attitude–Purchase Intention Relationship at Three Levels of Internet Literacy



Note. Slopes are the standardised conditional effects reported in Table 7.

In summary, all eight hypotheses were supported: PU and PEOU predicted attitude (H1, H3) and intention (H2, H4), attitude predicted intention (H5) and partially mediated the effects of PU and PEOU (H6, H7), and internet literacy strengthened the attitude–intention relationship (H8).

Discussion and Conclusion

Discussion of Findings

This study utilized an exploratory design with an aim to explore the interaction amongst the perception of technology, attitude & internet literacy and their influence on the intention to buy online among online shoppers in Pakistan. All eight hypotheses were confirmed and the model accounted for 69.1% of the variance of attitude and 74.1% of the variance of intention. As in TAM (Davis et al., 1989), and supported by previous study in Pakistan (Saleem et al., 2022), the attitude was highly influenced by perceived usefulness (β = .706) as compared to ease of use (β = .412). The pattern is appropriate for the online-shopping context, where instrumental benefits – such as saving money and time, and larger choice – are more influential in evaluations than effort considerations (Childers et al., 2001), and is consistent with recent findings from South Asia that evaluations are influenced by usefulness and ease of use (Islam et al., 2023).

Attitude mediated intention and had a moderate indirect effect on intention for both beliefs, accounting for approximately 43% of the total effect of both beliefs. The attitude is thus an important but not exclusive route: usefulness and ease of use also directly influence intention. This is consistent with the original finding that usefulness impacts on intention as well as attitude (Davis et al., 1989) and also endorses the inclusion of attitude in consumer applications of TAM rather than its exclusion (as in TAM2) (Venkatesh & Davis, 2000). The finding of the significant direct effect of ease of use on intention (β = .198) contradicts the findings of Nazzal et al. (2021) in Palestinian evidence, where ease of use did not predict intention to purchase online, but it was in line with the findings of Islam et al. (2023) in Bangladeshi evidence. Variations could indicate market maturity and usage differences with platform, which could be tested with future comparative work.

Internet literacy was the strongest direct predictor of intention (β = .441), exceeding attitude and usefulness, and it positively moderated the attitude–intention relationship. The direct effect is consistent with Nazzal et al. (2021) and with research on second-level digital divides showing that skills influence what people do online (Hargittai & Hsieh, 2012; van Deursen & van Dijk, 2019); it suggests that skills shape not only how people use the internet but also whether they plan to buy through it. The moderation result agrees with Restianto et al. (2024), who found that digital literacy conditioned the link between user satisfaction and continued e-commerce use. In planned-behaviour terms, skilled consumers perceive greater control over the buying process and therefore act more fully on their evaluations (Ajzen, 1991; Compeau & Higgins, 1995), whereas attitudes held by less-skilled consumers are less readily converted into intention. The interaction effect was small (f^2 = 0.049), as interaction effects in field studies typically are (Aguinis et al., 2005), but it is substantively meaningful: the effect of attitude was .460 at high and .248 at low literacy.

One feature of the data deserves attention. PU and PEOU were almost uncorrelated (r = .04), whereas TAM posits that ease of use influences usefulness and meta-analyses report substantial associations between the two (King & He, 2006; Schepers & Wetzels, 2007). This independence explains why both beliefs had distinct effects on attitude with no collinearity (VIF = 1.00), but it departs from typical TAM findings and should be replicated before it is interpreted substantively. Together with the very high reliabilities (ρ*c* up to .975), it may indicate a homogeneous response pattern within constructs, which future samples should examine.

Theoretical Implications

The findings have three theoretical implications. First, they support retaining attitude as an explicit mediating mechanism in TAM-based models of online shopping, because roughly two-fifths of the total effects of PU and PEOU on intention operate through it. Second, they show that competence is a boundary condition of the attitude–intention link, which connects TAM to the theory of planned behaviour (Ajzen, 1991, 2020) and to the digital-divide literature (van Deursen & van Dijk, 2019): beliefs and attitudes explain whether consumers want to shop online, whereas skills help explain whether wanting converts into intending. Third, the study extends TAM evidence to Pakistani online shoppers using current PLS-SEM reporting standards, including explicit common-method-bias diagnostics (Kock, 2015; Podsakoff et al., 2024).

Practical Implications

But, for the ecommerce operator, usefulness is the strongest demographic driver of attitude, and thus platforms should clearly and reliably demonstrate benefits in price comparison, delivery tracking, large selection of products, and straightforward return policies. Ease of use is still very important since it has a direct impact on intention and via attitude; mobile first and easier navigation and checkout are therefore worth having. The attitude–intention relationship is stronger when consumers are skilled, therefore, positive attitudes will not lead to positive intentions by less-skilled consumers. The skill level required to purchase can be reduced through guided first purchases, in-app tutorials, transparent security prompts and fraud awareness messaging. The strong direct link between literacy and a skills gap highlights that e-skills programmes can be used as a tool for enabling e-commerce participation, in addition to investments in connectivity (Kemp, 2025; van Deursen & van Dijk, 2019).

Limitations and Future Research

There are several caveats to the results. First, the cross-sectional design does not allow for causal interpretations, and intention is only a weak predictor of behavior (Sheeran & Webb, 2016) which means a longitudinal or experimental design with intention and actual purchases would be more informative. Second, a convenience sample, almost exclusively male and female, highly educated, and from two cities, reduces the generalisability of the findings to older, rural, and less digitally engaged consumers, and multigroup analyses and probability sampling are recommended. Third, while there is no evidence of method bias in the Harman's test or from the full collinearity VIFs, the use of a single source to collect data and self-reports does not exclude the possibility of method bias (Podsakoff et al., 2012, 2024); future studies should utilize multiple sources of data, multiple marker variables, and behavioural data. Fourth, loadings above .90 and composite reliabilities above .95 for three constructs suggest some item redundancy, so shorter scales should be tested, and internet literacy was measured as a self-assessed, unidimensional construct; performance-based and multidimensional measures would be preferable (Ng, 2012; van Laar et al., 2017). Fifth, the model omitted trust, perceived risk, and social influence, which are prominent in online-shopping research (Gefen et al., 2003; Majeed et al., 2024; Pavlou, 2003), and it was not evaluated for out-of-sample predictive power (Shmueli et al., 2019). Finally, the near-zero correlation between PU and PEOU should be examined in new samples.

Conclusion

This study shows that, among Pakistani online shoppers, perceived usefulness and ease of use shape online purchase intention both directly and through attitude, and that internet literacy not only boosts intention directly but also strengthens the translation of attitude into intention. By integrating mediation and moderation in one model, the study indicates that influencing what consumers think about online shopping is necessary but not sufficient: consumers also need the skills to act on favourable attitudes. E-commerce operators and policymakers should therefore pair usefulness and usability improvements with digital-skills support, and future research should test the model with probability samples, behavioural outcomes, and richer measures of literacy.

References

Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of Applied Psychology, 90*(1), 94–107. https://doi.org/10.1037/0021-9010.90.1.94

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies,* 2(4), 314–324. https://doi.org/10.1002/hbe2.195

Bhatti, H. Y., Bint E. Riaz, M., Nauman, S., & Ashfaq, M. (2022). Browsing or buying: A serial mediation analysis of consumer's online purchase intentions in times of COVID-19 pandemic. *Frontiers in Psychology, 13*, Article 1008983. https://doi.org/10.3389/fpsyg.2022.1008983

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing, 77*(4), 511–535. https://doi.org/10.1016/S0022-4359(01)00056-2

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14*(2), 189–217. https://doi.org/10.1287/isre.14.2.189.16018

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189–211. https://doi.org/10.2307/249688

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Drolet, A. L., & Morrison, D. G. (2001). Do we really need multiple-item measures in service research? *Journal of Service Research, 3*(3), 196–204. https://doi.org/10.1177/109467050133001

Eshet-Alkalai, Y. (2004). Digital literacy: A conceptual framework for survival skills in the digital era. *Journal of Educational Multimedia and Hypermedia, 13*(1), 93–106.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research, 69*(8), 3192–3198. https://doi.org/10.1016/j.jbusres.2015.12.008

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90. https://doi.org/10.2307/30036519

Glasman, L. R., & Albarracín, D. (2006). Forming attitudes that predict future behavior: A meta-analysis of the attitude–behavior relation. *Psychological Bulletin, 132*(5), 778–822. https://doi.org/10.1037/0033-2909.132.5.778

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hargittai, E. (2002). Second-level digital divide: Differences in people's online skills. *First Monday, 7*(4). https://doi.org/10.5210/fm.v7i4.942

Hargittai, E., & Hsieh, Y. P. (2012). Succinct survey measures of web-use skills. *Social Science Computer Review, 30*(1), 95–107. https://doi.org/10.1177/0894439310385538

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling, 17*(1), 82–109. https://doi.org/10.1080/10705510903439003

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Islam, S., Islam, M. F., & Zannat, N.-E. (2023). Behavioral intention to use online for shopping in Bangladesh: A technology acceptance model analysis. *SAGE Open, 13*(3). https://doi.org/10.1177/21582440231197495

Kemp, S. (2025). *Digital 2025: Pakistan*. DataReportal. https://datareportal.com/reports/digital-2025-pakistan

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). Guilford Press.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal, 28*(1), 227–261. https://doi.org/10.1111/isj.12131

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems, 13*(7), 546–580. https://doi.org/10.17705/1jais.00302

Majeed, M. U., Aftab, H., Arslan, A., & Shakeel, Z. (2024). Determining online consumer's luxury purchase intention: The influence of antecedent factors and the moderating role of brand awareness, perceived risk, and webatmospherics. *PLOS ONE, 19*(2), Article e0295514. https://doi.org/10.1371/journal.pone.0295514

Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). Moderation analysis: Issues and guidelines. *Journal of Applied Structural Equation Modeling, 3*(1), i–xi. https://doi.org/10.47263/JASEM.3(1)01

Nazzal, A., Thoyib, A., Zain, D., & Hussein, A. S. (2021). The influence of digital literacy and demographic characteristics on online shopping intention: An empirical study in Palestine. *Journal of Asian Finance, Economics and Business, 8*(8), 205–215. https://doi.org/10.13106/jafeb.2021.vol8.no8.0205

Ng, W. (2012). Can we teach digital natives digital literacy? *Computers & Education, 59*(3), 1065–1078. https://doi.org/10.1016/j.compedu.2012.04.016

Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems, 116*(9), 1849–1864. https://doi.org/10.1108/IMDS-07-2015-0302

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*, 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior, 11*, 17–61. https://doi.org/10.1146/annurev-orgpsych-110721-040030

Restianto, Y. E., Suliyanto, Naufalin, L. R., Krisnaresanti, A., Dinanti, A., Iskandar, D., & Sugiyono. (2024). User experience and behavioral intention to use e-commerce: A study of digital literacy as a moderating variable. *Journal of Governance and Regulation, 13*(1), 8–17. https://doi.org/10.22495/jgrv13i1art1

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4* [Computer software]. SmartPLS. https://www.smartpls.com

Saleem, A., Aslam, J., Kim, Y. B., Nauman, S., & Khan, N. T. (2022). Motives towards e-shopping adoption among Pakistani consumers: An application of the technology acceptance model and theory of reasoned action. *Sustainability, 14*(7), Article 4180. https://doi.org/10.3390/su14074180

Saoula, O., Hamid, A. B. A., Bhatti, M. A., Meng, L. K., Alwi, S. F. S., & Ahmad, M. F. (2023). Building e-trust and e-retention in online shopping: The role of website design, security, and authenticity. *Asia Pacific Journal of Marketing and Logistics, 35*(3), 572–599. https://doi.org/10.1108/APJML-08-2021-0577

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology & Marketing, 39*(5), 1035–1064. https://doi.org/10.1002/mar.21640

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management, 44*(1), 90–103. https://doi.org/10.1016/j.im.2006.10.007

Sheeran, P., & Webb, T. L. (2016). The intention–behavior gap. *Social and Personality Psychology Compass, 10*(9), 503–518. https://doi.org/10.1111/spc3.12265

Shiau, W.-L., Sarstedt, M., & Hair, J. F. (2019). Internet research using partial least squares structural equation modeling (PLS-SEM). *Internet Research, 29*(3), 398–406. https://doi.org/10.1108/IntR-10-2018-0447

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Streukens, S., & Leroi-Werelds, S. (2016). Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results. *European Management Journal, 34*(6), 618–632. https://doi.org/10.1016/j.emj.2016.06.003

Van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2019). The first-level digital divide shifts from inequalities in physical access to inequalities in material access. *New Media & Society, 21*(2), 354–375. https://doi.org/10.1177/1461444818797082

Van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior, 72*, 577–588. https://doi.org/10.1016/j.chb.2017.03.010

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178. https://doi.org/10.2307/41410412

Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197–206. https://doi.org/10.1086/651257

Appendix A

Measurement Items and Item-Level Statistics

Table A1: Item Wording, Descriptive Statistics, and Outer Loadings

Item	Wording	*M*	*SD*	Skew	Kurt.	Loading
Perceived usefulness						
PU1	Using online shopping platforms enables me to accomplish my purchases more quickly.	3.42	0.89	−0.19	−0.18	.937
PU2	Using online shopping platforms improves my overall shopping performance.	3.45	0.92	−0.22	−0.29	.942
PU3	Online shopping increases my productivity in managing daily purchases.	3.42	0.85	−0.06	−0.28	.928
PU4	Online shopping platforms provide me with access to a wider range of products than physical stores.	3.43	0.89	−0.14	−0.45	.932
PU5	I find online shopping to be useful for saving time and money.	3.46	0.85	−0.18	−0.06	.921

Item	Wording	*M*	*SD*	Skew	Kurt.	Loading
PU6	Overall, I believe that online shopping is a productive tool for making informed purchasing decisions.	3.42	0.86	0.00	−0.48	.923
Perceived ease of use						
PEOU1	I find it easy to navigate and browse products on online shopping platforms.	3.39	0.80	−0.22	0.18	.921
PEOU2	Learning to use online shopping platforms requires minimal effort.	3.39	0.84	−0.15	−0.08	.915
PEOU3	Online shopping platforms are clear and understandable in their interface design.	3.38	0.80	−0.15	0.18	.923
PEOU4	I find it easy to complete transactions (e.g., payment, checkout) on online shopping platforms.	3.33	0.82	−0.22	0.11	.937
PEOU5	Interacting with online shopping platforms does not require much mental effort.	3.37	0.85	−0.10	0.05	.926
PEOU6	Overall, I find online shopping platforms easy to use.	3.36	0.80	−0.06	−0.06	.908
Attitude toward online shopping						
AT1	I believe that shopping online is a good idea.	3.23	0.65	−0.08	0.20	.890
AT2	I have a positive overall evaluation of purchasing products through online platforms.	3.21	0.67	0.06	−0.21	.886
AT3	Shopping online is a wise choice for me given my needs and preferences.	3.25	0.64	−0.09	−0.37	.900
AT4	I feel favourably disposed toward engaging in online shopping activities.	3.24	0.65	−0.19	0.00	.907
Online purchase intention						
OPI1	I intend to purchase products through online shopping platforms in the near future.	4.13	0.67	−0.15	−0.77	.925
OPI2	I would consider buying products online the next time I need to make a purchase.	4.12	0.65	−0.13	−0.63	.910
OPI3	My willingness to engage in online purchasing activities is high.	4.13	0.65	−0.13	−0.65	.915
Internet literacy						
IL1	I am confident in my ability to find and evaluate product information on online shopping platforms.	3.50	0.87	−0.09	−0.29	.929
IL2	I can effectively assess the credibility and reliability of online shopping websites.	3.50	0.86	−0.14	−0.27	.927
IL3	I possess the navigational skills needed to complete online shopping transactions without difficulty.	3.47	0.84	−0.14	−0.19	.932
IL4	I am able to critically evaluate online product reviews and make informed purchasing decisions.	3.44	0.90	−0.05	−0.46	.933
IL5	I have the digital skills required to protect my personal and financial information during online transactions.	3.52	0.88	−0.21	−0.14	.945

Note. N = 240. Items were rated on five-point Likert scales (1 = *strongly disagree*, 5 = *strongly agree*). Skew = skewness; Kurt. = excess kurtosis. All loadings were significant at $p < .001$ (5,000-subsample bootstrap).



2026 by the authors; Journal of *Kashmir Journal of Academic Research and Development*. This is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) license (http://creativecommons.org/licenses/by/4.0/).