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BEYOND PURCHASE INTENTION: EXPLAINING ACTUAL BUYING BEHAVIOUR THROUGH DIGITAL INFLUENCE AND SOCIAL MEDIA LITERACY

Iqra Babar[1], Yasir Aftab Farooqi[*2], Waqas Manzoor[3], Sheraz Anjum[4], Sameed Javed[5], M. Dilawar Warriach[6]

[1]*Lecturer, Faculty of Management and Administration Sciences (FMAS) University of Gujrat, Pakistan.*
[*2,3]*Assistant Professor, Faculty of Management and Administration Sciences (FMAS) University of Gujrat, Pakistan.*
[4]*Lecturer, Punjab College (UCP), Gujrat, Pakistan.*
[5,6]*BBA Graduate, Faculty of Management Sciences, UCP Constituent Campus, Gujrat, Pakistan.*

[1]iqra.babar@uog.edu.pk, [*2]yasir.aftab@uog.edu.pk, [3]waqas.manzoor@uog.edu.pk, [4]sheraz153@hotmail.com, [5]sameed.javaid.716@gmail.com

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Abstract

Social media has become a major route to purchase in Pakistan, but it is unclear how digital influence turns into completed purchases and for whom. Integrating source credibility theory, the theory of planned behaviour, and the persuasion knowledge model, this study tests a moderated-mediation model in which attitude toward brand and purchase intention mediate the effect of digital influence on actual buying behaviour, and social media literacy moderates the intention–behaviour link. Survey data from 410 social media users aged 18–40 in Punjab, Pakistan, were analysed with partial least squares structural equation modelling (SmartPLS 4; 5,000 bias-corrected and accelerated bootstrap resamples). Digital influence strongly predicted attitude toward brand (β = .724) and purchase intention (β = .716) and retained a small direct effect on buying behaviour (β = .165). Attitude (β = .275) and intention (β = .397) predicted buying behaviour, and both mediated the effect of digital influence (indirect β = .199 and .284), jointly carrying about 75% of its total effect (β = .648). Social media literacy had no main effect but positively moderated the intention–behaviour relationship (β = .407): intention strongly predicted behaviour at high literacy (β = .804) and not at low literacy (β = −.010). The model explained 71.7% of the variance in buying behaviour. Discriminant validity was satisfactory, but the literacy construct showed unstable bootstrap loadings, which qualifies the moderation estimate and is discussed. The findings show that influence converts into purchases mainly through intention and attitude and that this conversion depends on consumers' competence

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1. INTRODUCTION

Social media platforms have become a primary arena in which consumers discover, evaluate, and buy products, with influencer content, algorithmic recommendation, and peer engagement shaping brand exposure on a scale unseen in conventional retail (Leung et al., 2022; Vrontis et al., 2021). Pakistan illustrates this shift. It had a population of 241.49 million at the 2023 census, of which 127.69 million lived in Punjab (Pakistan Bureau of Statistics, 2023), and tens of millions of its residents were active social media users in 2024 (Kemp, 2024). For brand managers, however, exposure is not a sale: consumers first form attitudes and intentions, and many never complete a purchase. Studies consistently show that intentions are only moderately predictive of behaviour (Armitage & Conner, 2001; Sheeran, 2002; Sheeran & Webb, 2016), and recent influencer research reports that intentions generated by influencers convert only weakly into purchases (Mwainyekule, 2025).

Two gaps limit what is known about this conversion. First, research on influencer effects typically examines either direct effects on purchase intention (Ao et al., 2023; Lou & Yuan, 2019) or a single mediator such as brand attitude (Al-Mu'ani et al., 2023; Zhao et al., 2024), and it seldom models actual buying behaviour or compares attitudinal and intentional routes in one framework. Second, the competencies that enable consumers to act on their intentions are rarely examined. Social media literacy, the ability to analyse, evaluate, and participate competently in social media environments (Cho et al., 2024; Livingstone, 2004), may determine whether favourable intentions become completed purchases, yet it has not been tested as a boundary condition on the intention–behaviour link. Finally, most evidence comes from Western and East Asian markets, and Pakistani evidence is scarce.

This study addresses these gaps with three research questions: (RQ1) Does digital influence affect attitude toward brand, purchase intention, and actual buying behaviour? (RQ2) Do attitude toward brand and purchase intention mediate the effect of digital influence on actual buying behaviour? (RQ3) Does social media literacy moderate the effect of purchase intention on actual buying behaviour? The study contributes in three ways. It integrates source credibility theory, the theory of planned behaviour, and the persuasion knowledge model into one moderated-mediation model; it provides structural evidence for Punjab, Pakistan, using current PLS-SEM reporting standards (Hair et al., 2019; Sarstedt et al., 2022); and it identifies the conditions under which intention converts into purchase, which is directly useful for digital marketers.

2. Theoretical Background and Hypotheses

2.1 Constructs

Digital influence is the persuasive impact of social media influencers and platform-native content on consumers' brand-related cognitions and behaviour. Its effectiveness rests on perceived credibility, informational value, authenticity, and similarity to the follower, which together foster parasocial relationships and trust (Lou & Yuan, 2019; Liu & Zheng, 2024). *Attitude toward brand* is the favourable or unfavourable evaluation of a brand formed from cognitive beliefs and affective responses. *Purchase intention* is the self-reported likelihood of buying, a proximal predictor of purchase (Ajzen, 1991). *Actual buying behaviour* is the completed act of purchase, which is distinct from intention because it requires action and, on social platforms, can also arise impulsively (Nyrhinen et al., 2024). *Social media literacy* is a multidimensional competency covering critical analysis, evaluation, and competent participation in social media environments (Cho et al., 2024; Wendt et al., 2023).

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2.2 Theoretical Framework

Three theories are combined. Source credibility theory (Hovland & Weiss, 1951; Ohanian, 1990) holds that persuasion depends on the perceived credibility of the source, so credible influencers should shape brand evaluations and intentions. The theory of planned behaviour (Ajzen, 1991) positions attitude as a determinant of intention and intention as the proximal determinant of behaviour, which justifies the attitude and intention routes from influence to behaviour; the theory also allows perceived control, shaped by skills and resources, to condition the translation of intention into action. The persuasion knowledge model (Friestad & Wright, 1994) argues that consumers' knowledge of persuasion tactics and of the environment determines how they cope with persuasion attempts, which makes consumers' competence in the social media environment a natural moderator (Boerman et al., 2017).

2.3 Hypotheses

Digital influence, attitude, and intention (H1, H3)

When influencers are seen as credible and informative, followers evaluate the brands they promote more favourably and are more willing to buy them (Al-Mu'ani et al., 2023; Zhao et al., 2024; Jabbar et al., 2026). A meta-analysis of influencer research confirmed a consistent positive effect of influencer-driven engagement on purchase intention across contexts (Ao et al., 2023), and credibility mechanisms operate in China through parasocial relationships and perceived brand credibility (Liu & Zheng, 2024).

H1. Digital influence has a positive effect on attitude toward brand.

H3. Digital influence has a positive effect on purchase intention.

Effects on actual buying behaviour (H2, H4, H5)

Under the theory of planned behaviour, attitude and intention should predict behaviour (Ajzen, 1991), although the intention–behaviour link is often weaker than assumed (Sheeran & Webb, 2016) and was weak in a recent influencer study (Mwainyekule, 2025). Digital influence may also affect buying directly, because social media exposure triggers purchases that bypass deliberate intention formation (Nyrhinen et al., 2024; Rashid et al., 2026; Naeem et al., 2026). The three paths into buying behaviour are therefore retained.

H2. Digital influence has a positive direct effect on actual buying behaviour.

H4. Attitude toward brand has a positive effect on actual buying behaviour.

H5. Purchase intention has a positive effect on actual buying behaviour.

Parallel mediation (H6, H7)

If digital influence shapes attitude and intention (H1, H3) and these shape behaviour (H4, H5), they should transmit part of its effect. Attitude has been shown to carry influencer effects to purchase intention (Al-Mu'ani et al., 2023; Zhao et al., 2024). Because the direct path is also expected (H2), partial mediation is anticipated.

H6. Attitude toward brand mediates the effect of digital influence on actual buying behaviour.

H7. Purchase intention mediates the effect of digital influence on actual buying behaviour.

Social media literacy as a boundary condition (H8)

Acting on an intention to buy online requires judging seller credibility, comparing offers, handling payment, and protecting personal data, all of which depend on competence in the social media environment (Cho et al., 2024; Livingstone, 2004). Consumers with high literacy should therefore translate intentions into purchases more reliably, whereas intentions held by less literate consumers should convert less readily. This reasoning follows the theory of planned behaviour's emphasis on perceived control and the persuasion knowledge model's emphasis on environmental knowledge (Ajzen, 1991; Friestad & Wright, 1994). Literacy is also specified as a

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direct predictor of behaviour so that the interaction is estimated net of its main effect (Memon et al., 2019); this path is a control rather than a hypothesis.

Figure 1 presents the model.

H8. Social media literacy positively moderates the effect of purchase intention on actual buying behaviour, such that the effect is stronger at higher levels of literacy.

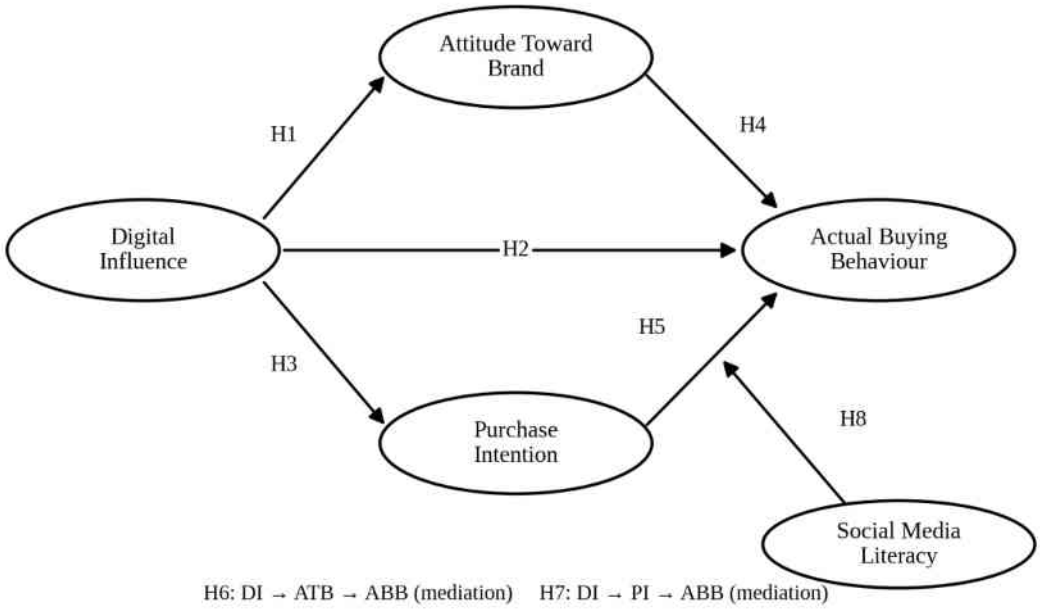


Figure 1 Conceptual Model and Hypotheses

Note. DI = digital influence; ATB = attitude toward brand; PI = purchase intention; ABB = actual buying behaviour; SML = social media literacy. H6 and H7 are the specific indirect effects of DI on ABB through ATB and PI.

3. Method

3.1 Research Design, Population, and Sampling

A cross-sectional survey design within a positivist, deductive approach was used (Saunders et al., 2023). The target population was social media users aged 18–40 who live in Punjab, Pakistan, and who have made at least one online purchase influenced by social media content. Individuals aged 18–40 form a very large share of the provincial population, and social media users in Pakistan number in the tens of millions (Kemp, 2024; Pakistan Bureau of Statistics, 2023), so the frame is large and accessible. No sampling frame of such users exists, so purposive sampling supplemented by snowball referral was used (Etikan et al., 2016). A structured questionnaire was distributed online through social media groups and university networks, and screening questions removed ineligible respondents. The analytic sample comprised N = 410 valid responses with no missing data.

Sample adequacy was assessed in three ways. A power analysis in GPower 3.1 (Faul et al., 2009) for the largest regression in the model (actual buying behaviour, five predictors including the interaction; $\alpha = .05$; power = .80) requires 55 cases for a medium effect ($f^2 = .15$) and 159 cases for a small-to-medium effect ($f^{*2} = .05$). The inverse square root method (Kock & Hadaya, 2018)

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indicates that 410 cases can detect path coefficients of about .12 at 80% power. The sample also far exceeds the ten-times guideline for PLS-SEM (Hair et al., 2022).

3.2 Measures

All constructs were measured with reflective multi-item scales on five-point Likert scales (1 = strongly disagree, 5 = strongly agree): digital influence (8 items; adapted from Liu & Zheng, 2024, and Zhao et al., 2024), attitude toward brand (5 items; adapted from Zhao et al., 2024), purchase intention (4 items; adapted from Mwainyekule, 2025), social media literacy (6 items; adapted from Wendt et al., 2023), and actual buying behaviour (5 items; adapted from Nyrhinen et al., 2024). In total, 28 indicators were used (Appendix A). Participation was voluntary and anonymous, and informed consent was obtained before data entry.

3.3 Common Method Bias

Because all constructs were self-reported at one-time point, procedural remedies were applied (anonymity, no right or wrong answers, and simple wording; Podsakoff et al., 2012). Statistical checks comprised Harman's single-factor test (Podsakoff et al., 2003) and a full-collinearity assessment in which VIFs of 3.3 or lower indicate that the model is free of pervasive method bias (Kock, 2015). Because Harman's test is insensitive (Fuller et al., 2016), it was interpreted together with the VIF criterion.

3.4 Data Analysis

The model was estimated with PLS-SEM in SmartPLS 4 (Ringle et al., 2024), which suits prediction-oriented models with several reflective constructs, mediation, and moderation (Hair et al., 2019; Shiau et al., 2019). The path weighting scheme was used (maximum 3,000 iterations; stop criterion 10^{-7}). Significance was assessed with two-tailed bootstrapping (5,000 subsamples) and bias-corrected and accelerated (BCa) 95% confidence intervals (Streukens & Leroi-Werelds, 2016). The measurement model was evaluated following Hair et al. (2019, 2020): outer loadings of at least .708; Cronbach's α, ρa, and ρc between .70 and .95 (values above .95 may signal redundant items; Drolet & Morrison, 2001); AVE above .50; the Fornell–Larcker criterion (Fornell & Larcker, 1981); and HTMT below .85 (Henseler et al., 2015). The structural model was assessed through inner VIFs (below 3.3), path coefficients, R^2, f^2 (.02, .15, and .35 denote small, medium, and large effects; Cohen, 1988), and model fit (SRMR, dULS, dG; Henseler et al., 2016). Mediation was classified from the direct and specific indirect effects (Nitzl et al., 2016; Zhao et al., 2010). Moderation was tested with the product-indicator approach (Henseler & Chin, 2010) and probed with simple slopes at ±1 SD of the moderator (Memon et al., 2019). Because the moderator proved weakly determined in the PLS algorithm (Section 4.3), the interaction was also re-estimated as a robustness check by ordinary least squares on standardised construct scores, with 5,000 percentile bootstrap resamples.

4. Results

4.1 Data Screening and Common Method Bias

The 410 retained cases had no missing values. Item skewness ($|\text{skew}| \leq 0.19$) and excess kurtosis ($|\text{kurtosis}| \leq 0.47$) were well within acceptable limits (Kline, 2023; Table A1). Harman's single-factor test showed that the first unrotated factor explained 48.5% of the variance in the 28 items, below the 50% criterion but close to it. In the full-collinearity assessment (Kock, 2015), the VIFs were 3.28 for digital influence and 1.00–2.25 for the other constructs, so none exceeded 3.3, although digital influence lay at the limit. Taken together, these diagnostics do not indicate a pervasive common method bias, but the proximity to both thresholds means that bias cannot be ruled out and is acknowledged as a limitation.

4.2 Measurement Model

Table 1 reports the measurement model. Outer loadings of digital influence, attitude toward brand, purchase intention, and actual buying

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behaviour ranged from .892 to .917 and were significant ($p < .001$). Cronbach's α (.934–.966), ρa (.935–.966), and ρc (.953–.971) were high, and AVE values (.808–.835) were well above .50. These values indicate excellent reliability and convergent validity, although ρc exceeded .95 for all four of these constructs (and α for digital influence) and indicator VIFs (3.30–4.34) were at or above 3.3 while remaining below 5, which suggests some item redundancy (Drolet & Morrison, 2001; Hair et al., 2019).

The social media literacy scale was internally consistent (inter-item r = .75–.79; α = .954; ρc = .931; AVE = .695), and its original-sample loadings (.698–.930) exceeded .70, although one (SML2) was only marginally above the threshold. However, the bootstrap distribution of its loadings was unstable: bootstrap standard deviations were about .18, and the BCa intervals of five of the six loadings included zero or negative values (for example, SML2: [−.461, .855]), which also produced an anomalous ρa (.155). This pattern arises because social media literacy was essentially uncorrelated with every other construct ($|r| \leq .063$), so the PLS algorithm determines its weights weakly. Because the six items themselves form a single dominant factor (first eigenvalue = 4.89 of 6; 81.5% of variance), the instability reflects the weighting scheme rather than poor items. Its consequences for the moderation estimate are examined in Section 4.6.

Table 1 Reliability and Convergent Validity of the Measurement Model

Construct	k	M	SD	Loadings	α	ρa	ρc	AVE
Digital influence	8	3.00	0.78	.892–.907	.966	.966	.971	.808
Attitude toward brand	5	3.00	0.79	.893–.913	.946	.946	.958	.821
Purchase intention	4	3.00	0.79	.911–.917	.934	.935	.953	.835
Social media literacy	6	3.01	0.77	.698–.930	.954	.155	.931	.695
Actual buying behaviour	5	3.01	0.76	.901–.913	.946	.946	.958	.821

Note. k = number of items; M and SD are for item-average construct scores (1–5 scale); α = Cronbach's alpha; ρa = reliability coefficient rho-A; ρc = composite reliability; AVE = average variance extracted. The ρa of social media literacy is unstable under bootstrapping (see text). N = 410.

4.3 Discriminant Validity

The square root of each construct's AVE (.834–.914) exceeded its correlations with all other constructs, satisfying the Fornell–Larcker criterion (Table 2). All HTMT ratios were below .85; the highest was between digital influence and attitude toward brand (.757; BCa 95% CI [.705, .802]), and the ratios involving social media literacy were at or below .041. Discriminant validity is therefore established, even though digital influence, attitude, intention, and buying behaviour are substantially correlated (r = .52–.72).

Table 2 Discriminant Validity: Fornell–Larcker Criterion and HTMT

Construct	1	2	3	4	5
1. Digital influence	.899	.757	.754	.035	.699
2. Attitude toward brand	.724	.906	.554	.039	.645
3. Purchase intention	.716	.520	.914	.041	.669

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Construct	1	2	3	4	5
4. Social media literacy	.036	.014	.009	.834	.032
5. Actual buying behaviour	.668	.610	.629	.063	.906

Note. Diagonal values are the square roots of AVE; values below the diagonal are latent variable correlations; values above the diagonal are HTMT ratios. The BCa intervals of HTMT ratios involving social media literacy are unreliable because of the unstable bootstrap distribution of that construct.

4.4 Structural Model and Direct Effects

Inner-model VIFs were between 1.00 and 3.20, below 3.3 (the highest was digital influence → buying behaviour; 95% bootstrap upper limit = 3.76), so collinearity among predictors was acceptable. The model explained 52.4% of the variance in attitude toward brand, 51.3% in purchase intention, and 71.7% in actual buying behaviour (adjusted R^2 = .523, .512, and .714), which is moderate to substantial (Hair et al., 2019). Model fit was good: SRMR = .042 (95% quantile = .081), dULS = .725 (2.689), and dG = .339 (.715), all below their bootstrap quantiles (Henseler et al., 2016).

Table 3 and Figure 2 report the direct effects. Digital influence had very large effects on attitude toward brand (H1: β = .724, t = 29.48, f^2 = 1.10) and on purchase intention (H3: β = .716, t = 32.84, f^2 = 1.05), both p < .001. Attitude (H4: β = .275, t = 6.82, f^2 = 0.13) and purchase intention (H5: β = .397, t = 8.57, f^2 = 0.27) predicted actual buying behaviour (p < .001), with intention the stronger predictor. Digital influence retained a small but significant direct effect on buying behaviour (H2: β = .165, t = 3.18, p = .001, f^2 = 0.03). Social media literacy had no significant main effect on buying behaviour (β = .043, p = .328). H1–H5 were therefore supported.

Table 3 Direct Effects and Hypothesis Tests

Path	β	SD	t	95% BCa CI	p	f^2	Decision
H1: DI → ATB	.724	.025	29.48	[.671, .768]	<.001	1.10	Supported
H3: DI → PI	.716	.022	32.84	[.670, .755]	<.001	1.05	Supported
H2: DI → ABB (direct)	.165	.052	3.18	[.049, .247]	.001	0.03	Supported
H4: ATB → ABB	.275	.040	6.82	[.214, .376]	<.001	0.13	Supported
H5: PI → ABB	.397	.046	8.57	[.310, .488]	<.001	0.27	Supported
Control: SML → ABB	.043	.044	0.98	[−.036, .124]	.328	0.01	—

Note. DI = digital influence; ATB = attitude toward brand; PI = purchase intention; SML = social media literacy; ABB = actual buying behaviour. β = standardised path coefficient; SD = bootstrap standard deviation; BCa CI = bias-corrected and accelerated confidence interval; p values are two-tailed (5,000 subsamples). N = 410.

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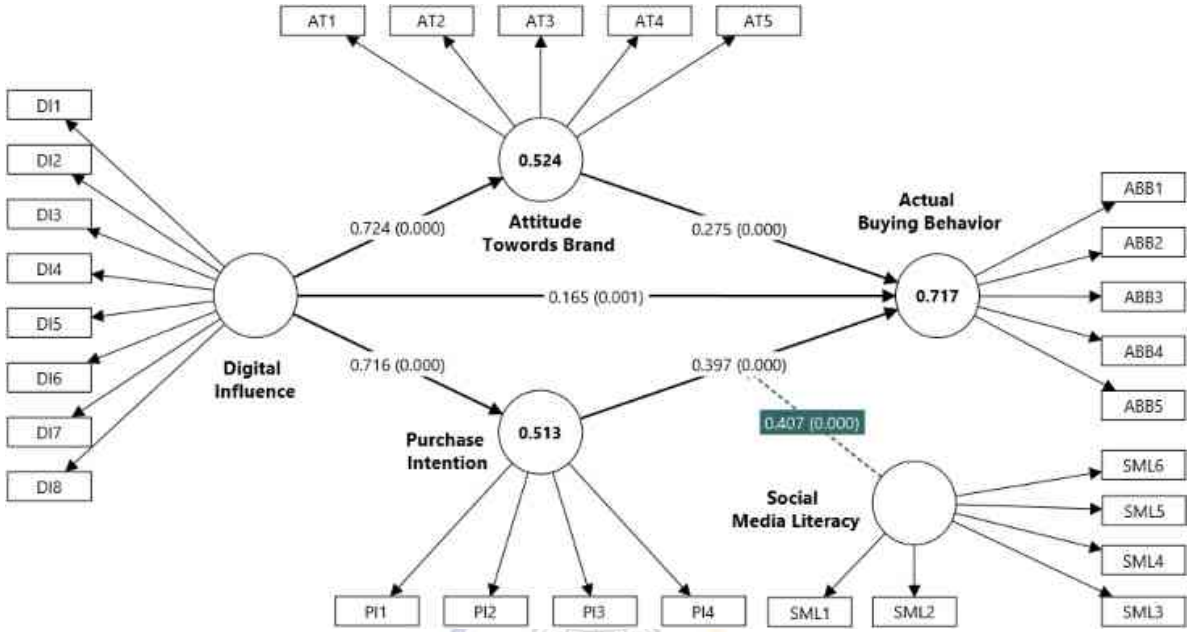


Figure 2 Structural Model Results With Standardised Path Coefficients

Note. Coefficients are bootstrapped standardised estimates (N = 410). The arrow from social media literacy points to the purchase intention → buying behaviour path (interaction effect). * p < .01. * p* < .001.

4.5 Mediation Analysis

Table 4 shows that the specific indirect effects of digital influence on buying behaviour through attitude (H6: β = .199, t = 6.50, 95% BCa CI [.153, .276]) and through purchase intention (H7: β = .284, t = 8.37, 95% BCa CI [.223, .352]) were significant. Because the direct effect was also significant and had the same sign, both mediations are complementary and partial (Nitzl et al., 2016; Zhao et al., 2010). The two indirect routes together accounted for 74.5% of the total effect of digital influence (β = .648, 95% BCa CI [.590, .704]), and the intention route carried a larger share (VAF = 43.8%) than the attitude route (30.7%). H6 and H7 were supported.

Table 4 Mediation Analysis: Specific Indirect, Direct, and Total Effects of Digital Influence on Actual Buying Behaviour

Effect	Estimate	SD	t	95% BCa CI	Total	VAF (%)
H6: DI → ATB → ABB	.199	.031	6.50	[.153, .276]	.648	30.7
H7: DI → PI → ABB	.284	.034	8.37	[.223, .352]	.648	43.8
Both indirect effects combined	.483				.648	74.5
Direct effect (H2)	.165	.052	3.18	[.049, .247]	.648	25.5

Note. VAF = variance accounted for (effect ÷ total effect). Both specific indirect effects were significant at p < .001 (two-tailed). The combined indirect effect is the sum of the two specific effects. N = 410.

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4.6 Moderation Analysis

The interaction between purchase intention and social media literacy had a significant positive effect on actual buying behaviour (H8: β = .407, t = 5.37, p < .001, 95% BCa CI [.265, .481]) with a large effect size (f^2 = 0.67), so H8 was supported. Table 5 and Figure 3 show the nature of the interaction. The effect of intention on behaviour was strong at high literacy (+1 SD: β = .804, t = 7.83, p < .001), moderate at mean literacy (β = .397, t = 8.57, p < .001), and absent at low literacy (−1 SD: β = −.010, t = 0.14, p = .891). The conditional indirect effect of digital influence through intention followed the same pattern (+1 SD: β = .576; mean: β = .284; −1 SD: β = −.007, n.s.).

Because the bootstrap behaviour of the literacy construct was unstable (Section 4.2), the interaction was re-estimated using standardised construct scores (item means) in a regression with 5,000 bootstrap resamples. This robustness check gave a very similar result: interaction β = .411 (95% percentile CI [.352, .474]; f^2 = 0.76), a simple slope of −.014 at low literacy (CI [−.107, .077]), and .808 at high literacy (CI [.706, .915]). The substantive conclusion is therefore robust to the estimation method, although the exact PLS coefficients and the f^2 of the interaction should be read with caution.

Table 5 Moderation Analysis: Interaction Effect and Conditional Effects of Purchase Intention on Actual Buying Behaviour

Effect	β	SD	t	p	95% BCa CI	Decision
H8: PI × SML → ABB	.407	.076	5.37	<.001	[.265, .481]	Supported
Conditional effect of PI on ABB						
Low SML (−1 SD)	−.010	.072	0.14	.891	[−.120, .135]	n.s.
Mean SML	.397	.046	8.57	<.001	[.310, .488]	Significant
High SML (+1 SD)	.804	.103	7.83	<.001	[.618, .928]	Significant
Conditional indirect effect: DI → PI → ABB						
Low SML (−1 SD)	−.007	.052	0.14	.891	[−.086, .096]	n.s.
Mean SML	.284	.034	8.37	<.001	[.223, .352]	Significant
High SML (+1 SD)	.576	.075	7.68	<.001	[.436, .676]	Significant

Note. SML = social media literacy; PI = purchase intention; DI = digital influence; ABB = actual buying behaviour; n.s. = not significant. N = 410.

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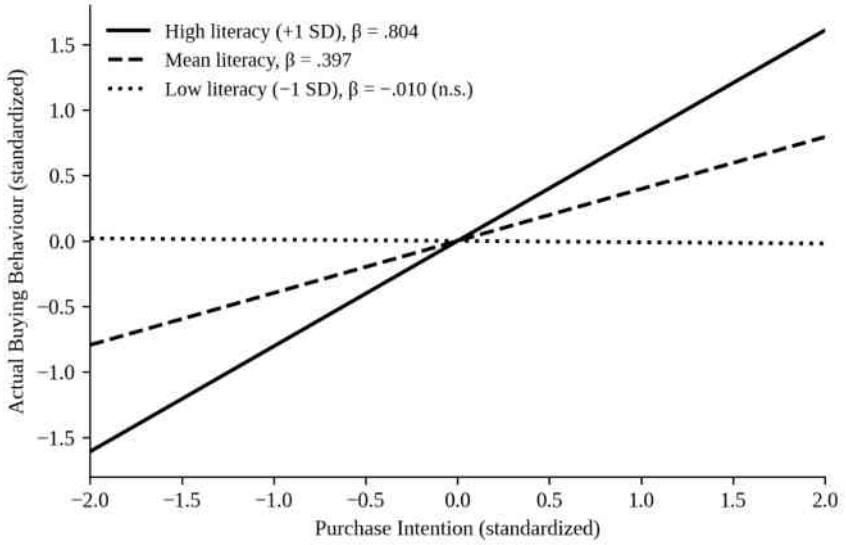


Figure 3Simple Slopes of Purchase Intention on Actual Buying Behaviour at Three Levels of Social Media Literacy

Note. Slopes are the standardised conditional effects reported in Table 5.
In summary, all eight hypotheses were supported.

5. Discussion and Conclusion

5.1 Discussion of Findings

This study examined how digital influence is converted into actual buying behaviour among social media users in Punjab, Pakistan, and under what conditions. All eight hypotheses were supported, and the model explained 71.7% of the variance in buying behaviour. Digital influence strongly shaped attitude toward brand and purchase intention (β = .724 and .716), consistent with source credibility theory and with evidence that influencer credibility improves brand evaluations and intentions (Al-Mu'ani et al., 2023; Liu & Zheng, 2024; Zhao et al., 2024). The size of these paths exceeds typical meta-analytic estimates (Ao et al., 2023), which may reflect the strong overlap among the influence, attitude, and intention items rather than an unusually powerful effect; HTMT values below .85 show that the constructs are distinguishable but not independent.

Attitude and intention both predicted buying behaviour, with intention the stronger predictor

(β = .397 vs. .275), in line with the theory of planned behaviour (Ajzen, 1991). This is a noticeably stronger intention–behaviour link than the weak conversion reported among London social media users (Mwainyekule, 2025) and than the moderate links in earlier syntheses (Armitage & Conner, 2001; Sheeran & Webb, 2016). A plausible explanation is that respondents were screened for having already purchased because of social media content, so that intentions rest on experience; the self-reported nature of both measures may also inflate the link. Both mediators carried part of the influence of digital influence, together about three-quarters of its total effect, so influence works mainly by shaping what consumers think and intend rather than by prompting purchases directly. The small residual direct effect (β = .165; f^2 = 0.03) is compatible with the impulsive purchasing described in young consumers' social media use (Nyrhinen et al., 2024) but is much smaller than the indirect routes. Social media literacy had no main effect on buying behaviour but strongly conditioned the effect of

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intention. At low literacy, intention did not predict behaviour (β = −.010), whereas at high literacy it did so strongly (β = .804). This pattern is consistent with the theory of planned behaviour's emphasis on perceived control and with the persuasion knowledge model, which highlights the importance of consumers' environmental knowledge (Ajzen, 1991; Boerman et al., 2017; Friestad & Wright, 1994). Consumers who can evaluate sellers, compare offers, and complete transactions act on their intentions, while those with less competence do not. The finding extends research that treats literacy as an antecedent of attitudes or of resistance to persuasion (Cho et al., 2024; Wendt et al., 2023) by showing that it is a boundary condition at the final step from intention to action. Because the literacy items were adapted from a scale of participatory-moral literacy (Wendt et al., 2023), the mechanism proposed here (practical fluency in purchasing) is an interpretation that future work should test with a purchase-specific literacy measure.

5.2 Theoretical Implications

The study offers three theoretical contributions. First, it shows that attitude and intention operate as parallel, complementary routes from digital influence to behaviour, with intention the dominant route, which refines single-mediator models of influencer effects (Al-Mu'ani et al., 2023; Zhao et al., 2024). Second, it identifies social media literacy as a boundary condition of the intention–behaviour link, offering one explanation for the intention–behaviour gap (Sheeran & Webb, 2016) that is specific to platform-based commerce. Third, it integrates source credibility theory, the theory of planned behaviour, and the persuasion knowledge model in one empirical model and tests it in an under-researched South Asian market.

5.3 Practical Implications

For marketers, credible influencers are the main lever for building both favourable brand attitudes and purchase intentions, so partnerships should be selected for credibility and authenticity rather than reach alone (Leung et al., 2022; Lou & Yuan, 2019). Because intention converts to purchase only among consumers who are competent in the social media environment, brands should reduce friction for less literate segments by simplifying checkout, offering visible seller verification and secure payment options, and providing guided purchase journeys. Platforms and policymakers can support conversion and consumer protection by investing in social media literacy programmes.

5.4 Limitations and Future Research

The findings are subject to several limitations. First, the cross-sectional, self-reported design precludes causal inference, and buying behaviour was reported rather than observed; longitudinal designs and transaction data would be more informative (Podsakoff et al., 2012, 2024). Second, Harman's first factor (48.5%) and the full-collinearity VIF of digital influence (3.28) lay close to their thresholds, and very high reliabilities (ρc > .95 for four constructs) and indicator VIFs above 3.3 suggest item redundancy, so some inflation of the structural paths cannot be excluded; shorter scales and marker-variable or multi-source designs are recommended. Third, the social media literacy construct was weakly determined in the PLS algorithm because it was uncorrelated with the other constructs; the robustness check supports the moderation result, but the exact coefficient and effect size are uncertain, and the construct should be re-measured with a purchase-specific, performance-based instrument. Fourth, non-probability sampling in one province limits generalisability to other regions and to consumers who do not shop through social media. Finally, the model omits factors such as trust, perceived risk, price, and platform type, and out-of-sample predictive power (Shmueli et al., 2019) was not assessed. Future studies should test the model across provinces and platforms, add trust and risk, and use experimental or panel designs.

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5.5 Conclusion

Among social media users in Punjab, digital influence strengthens purchase through two complementary routes, brand attitude and purchase intention, with intention the stronger, and a small direct route remains. Whether intention becomes a completed purchase depends on social media literacy: consumers with low literacy did not act on their intentions in this sample, whereas those with high literacy did. For brands, influence building should therefore be combined with efforts to make buying easy and safe for less literate consumers; for researchers, the results show that the intention–behaviour gap is conditional rather than uniform, and that the competencies consumers bring to digital environments merit more systematic study.

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Appendix A
Item-Level Statistics
Table A1
Descriptive Statistics, Outer Loadings, and Outer-Model VIFs for the Indicators

Item	M	SD	Skew	Kurt.	Loading	VIF
Digital influence						
DI1	3.00	0.91	−0.15	−0.21	.907	4.34
DI2	2.97	0.86	−0.03	0.05	.905	4.29
DI3	3.00	0.86	−0.03	0.00	.898	4.07
DI4	2.99	0.85	−0.08	−0.24	.901	4.08
DI5	3.01	0.85	−0.07	−0.11	.892	3.83
DI6	3.02	0.88	−0.12	−0.05	.896	3.93
DI7	3.01	0.87	−0.04	−0.36	.895	3.95
DI8	2.97	0.87	−0.11	−0.04	.899	4.06
Attitude toward brand						
AT1	3.01	0.88	−0.06	−0.21	.893	3.30
AT2	2.99	0.89	0.05	−0.11	.910	3.77
AT3	2.99	0.87	−0.08	−0.40	.906	3.68
AT4	3.01	0.85	−0.10	−0.19	.913	3.88
AT5	2.98	0.87	−0.03	−0.30	.909	3.69
Purchase intention						
PI1	3.00	0.86	−0.13	−0.25	.916	3.59
PI2	3.00	0.88	0.00	−0.35	.917	3.59
PI3	3.00	0.87	0.07	−0.27	.911	3.50
PI4	2.99	0.86	0.02	−0.24	.911	3.37
Social media literacy						
SML1	2.99	0.86	0.15	−0.13	.887	3.74
SML2	3.03	0.86	−0.01	−0.35	.698	3.65
SML3	3.00	0.85	−0.15	−0.37	.930	3.83
SML4	2.99	0.86	−0.05	−0.05	.802	4.02
SML5	3.00	0.87	0.19	−0.31	.863	3.71
SML6	3.03	0.85	0.06	−0.24	.800	3.91
Actual buying behaviour						
ABB1	3.02	0.83	−0.02	0.37	.905	3.58
ABB2	3.00	0.84	−0.02	0.09	.908	3.72
ABB3	3.01	0.83	−0.09	0.34	.901	3.43

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Item	M	SD	Skew	Kurt.	Loading	VIF
ABB4	3.02	0.83	0.14	0.29	.905	3.65
ABB5	3.00	0.83	0.06	0.47	.913	3.84

Note. N = 410. M = mean; SD = standard deviation; Skew = skewness; Kurt. = excess kurtosis; VIF = variance inflation factor. Loadings are original-sample PLS estimates; the bootstrap intervals of the SML loadings are unstable (see Section 4.2).