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Social Commerce as a Digital Enabler of Viksit Bharat: Women Consumers' Purchase Decision-Making in the Digital Era

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Abstract

India's vision of Viksit Bharat@2047 gives central importance to Digital inclusion, technological advancement and the economic participation of women. Social commerce now shapes how consumers search for information, evaluate products and make purchase choices. This study examines how digital literacy and perceived AI personalisation relate to the purchase decision-making of women social commerce users, with perceived value tested as a mediating mechanism. Drawing on an extended Stimulus-Organism-Response framework and the Value-based Adoption Model, primary data were collected from 129 women social commerce users through a structured questionnaire and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with the seminr package in R. Digital literacy and perceived AI personalisation were specified as higher-order constructs, and purchase decision-making was specified as a formative construct covering six purchase choices. Perceived AI personalisation was positively associated with perceived value ($\beta = 0.347$) and with purchase decision-making ($\beta = 0.457$). Digital literacy was not significantly associated with either outcome, and perceived value was not significantly associated with purchase decision-making. Neither mediation path was significant. The model explained 36.5% of the variance in purchase decision-making, and all indicators produced positive Q^2predict values, indicating predictive relevance. The findings suggest that, among the women in this sample, perceived AI personalisation was positively associated with purchase decision-making, whereas

the proposed perceived value pathway was not supported. The findings provide consumer-level evidence that can inform discussion of digital inclusion and women's participation in digital commerce within the Viksit Bharat@2047 agenda.

Keywords: Viksit Bharat@2047; social commerce; women consumers; digital literacy; perceived AI personalisation; perceived value; purchase decision-making; PLS-SEM

I. INTRODUCTION

India's Viksit Bharat@2047 vision aims to make the country a developed nation by the centenary of its independence. The Interim Union Budget 2024–25 identified four groups at the heart of this goal: the poor, women, youth and farmers (Ministry of Finance, 2024). Digital transformation is expected to carry much of this progress. The State of India's Digital Economy Report 2024 ranked India third globally in economy-wide digitalisation, but 12th among G20 countries in the digitalisation of individual users (Indian Council for Research on International Economic Relations [ICRIER], 2024). India had approximately 820 million internet users in 2023 (IAMAI and Kantar data, as reported in Kakaty & Sarkar, 2026). The gap between economy-wide and individual-level digitalisation shows why consumer-level participation, including that of women, deserves attention.Social commerce is one setting in which this participation takes place. It combines social media and online shopping, so that consumers discover, discuss and buy products within the same platform (Liang & Turban, 2011; Huang & Benyoucef, 2013; Lin et al., 2017). Platforms and social commerce channels such as Meesho, Instagram and WhatsApp-based selling allow consumers to discover products, communicate with sellers and complete purchases digitally. Two conditions are expected to relate to purchase decision-making in this setting. The first is the consumer's own capability. Digital literacy covers the technical, cognitive and social-emotional skills needed to use digital platforms (Ng, 2012), and it relates to the inclusion goal of Viksit Bharat. The second is how consumers experience the platform's technology. Perceived AI personalisation reflects the extent to which consumers see the products, content and browsing experience as tailored to them (Emini et al., 2025), and it relates to the innovation goal, as artificial intelligence is expected to play a central role in reaching the 2047 targets (Rehman et al., 2025). Both conditions are expected to be associated with the value consumers see in a platform, and value is widely treated as an antecedent of purchase behaviour (Zeithaml, 1988; Kim et al., 2007). Prior social commerce research has examined trust, social presence, social support and platform features (Hajli, 2015; Lu et al., 2016; Hajli et al., 2017; Zhang & Benyoucef, 2016; Dwivedi et al., 2023). Three areas appear underexamined. First, digital literacy and perceived AI personalisation have rarely been studied together as antecedents of purchase decision-making, even though one reflects the consumer and the other the

consumer's experience of the platform. Second, the role of perceived value as a link between these antecedents and purchase decision-making appears underexamined for women consumers in India. Third, empirical research connecting consumer-level social commerce behaviour with the Viksit Bharat@2047 policy context remains limited. This study addresses these areas with three research questions. (1) Are digital literacy and perceived AI personalisation associated with the perceived value and purchase decision-making of women social commerce users? (2) Is perceived value associated with their purchase decision-making? (3) Does perceived value mediate these relationships? The study tests a model with 129 women social commerce users using PLS-SEM. Viksit Bharat@2047 is treated as the policy context of the study rather than as an outcome tested by the model. Section 2 reviews the literature and develops the hypotheses. Sections 3 and 4 present the method and results, and Sections 5 to 8 discuss the findings, implications, limitations and conclusion.

Literature Review and Hypotheses Development

Theoretical background

The study draws on the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974). In this framework, environmental stimuli are associated with a person's internal evaluation (organism), which is in turn associated with behaviour (response). Perceived AI personalisation fits the stimulus role, as it captures how consumers experience the platform environment. Digital literacy is different, because it is a characteristic of the consumer rather than of the environment. The present study extends this framework by incorporating digital literacy as an individual-level antecedent alongside perceived AI personalisation as a platform-related stimulus. Perceived value represents the consumer's internal evaluation, and purchase decision-making represents the behavioural response. Social commerce studies have used S-O-R in a similar way to link platform attributes with internal states and purchase-related outcomes (Busalim et al., 2021). The Value-based Adoption Model (Kim et al., 2007) adds a specific account of the organism stage. It proposes that consumers adopt a technology when the benefits they receive outweigh the costs they give up, so perceived value becomes the main route linking technology features to behaviour. Together, the two frameworks provide the basis for expecting consumer capability and perceived personalisation to relate to purchase decision-making through perceived value.

Social commerce, women and Viksit Bharat@2047

In this study, social commerce refers to online purchasing activities in which social interaction, social content, recommendations, seller communication or community features are integrated into, or directly support, the buying process (Liang & Turban, 2011; Busalim & Hussin, 2016). This definition covers reseller platforms, social media shops and messaging-based selling, which differ in design

but share this social element. Consumers in developing economies still adopt social commerce unevenly, and ease of use, trust and support are associated with whether they continue (Sarker et al., 2025). In India, consumer perceptions of social commerce rest on usability, trust, price and perceived value (Vij & Kaur, 2025). For women consumers, these platforms can provide additional digital channels for product discovery, seller communication and purchasing without requiring a visit to a physical market. Their participation as digital consumers is part of the wider consumption base discussed under Viksit Bharat@2047 (Kakaty & Sarkar, 2026), and digital literacy and trust have been identified as foundations of long-term inclusion under this vision (Mohapatra & Ghosh, 2025).

Digital literacy and perceived value

Ng (2012) describes digital literacy through three intersecting dimensions: technical skills to operate devices and platforms, cognitive skills to search for and evaluate information, and social-emotional skills to communicate and protect oneself online. Consistent with this multidimensional structure, the present study models technical, cognitive and social-emotional literacy as lower-order dimensions of digital literacy. For the purposes of this study, these dimensions are specified as reflective first-order constructs forming a reflective higher-order digital literacy construct. Higher digital literacy may enable consumers to compare offers across sellers, read reviews critically and avoid poor-quality listings, which may be associated with a higher perceived value of the platform (Zeithaml, 1988; Sweeney & Soutar, 2001).

Hence:

H1: Digital literacy is positively associated with perceived value.

Perceived AI personalisation and perceived value

AI personalisation uses a consumer's past behaviour to tailor what the platform shows. Emini et al. (2025) describe several mechanisms, including recommendation accuracy, personalised content, interface customisation and conversational AI. Building on this work, the present study groups the consumer's perception of personalisation into three dimensions experienced in social commerce: product personalisation (which items are recommended), content personalisation (which offers, posts and promotions are shown) and experience personalisation (how the browsing interface adapts). For the purposes of this study, these dimensions are specified as reflective lower-order constructs of a reflective higher-order perceived AI personalisation construct. Relevant recommendations may reduce search effort and show products that match the consumer's needs, which may be associated with higher perceived value. Personalisation can also raise concerns about data use (Aguirre et al., 2015). Guo and Li (2022) found that social commerce features were positively related to perceived value.

Hence:

H2: Perceived AI personalisation is positively associated with perceived value.

Perceived value and purchase decision-making

Perceived value is the consumer's overall judgement of what is received against what is given (Zeithaml, 1988). The Value-based Adoption Model treats it as the main antecedent of adoption behaviour (Kim et al., 2007). Much social commerce research measures the behavioural outcome as purchase intention. A meta-analysis of studies from 2010 to 2022 found that perceived value correlates strongly with purchase intention (Wang & Shahzad, 2024), perceived value is among the strongest correlates of customer engagement on social commerce platforms (Busalim et al., 2021), and cognitive appraisal of a platform predicts purchase intention (Chen et al., 2017). The present study focuses on purchase decision-making rather than intention. Following the consumer decision framework associated with Kotler and Keller (2018), purchase decision-making encompasses choices concerning the product, brand or seller, channel, quantity, timing and payment method. Taufik (2021) provides supporting empirical evidence from purchase decision research. Intention reflects a plan to buy, while purchase decision-making reflects the choices made during buying. Evidence on intention is relevant because intention usually precedes these choices, but the two are not identical, and a value judgement associated with intention may not be associated with every purchase choice to the same extent. Hence:

H3: Perceived value is positively associated with purchase decision-making.

Direct relationships with purchase decision-making

Capability and perceived personalisation may also relate to purchase decision-making directly. Higher digital literacy may enable consumers to complete online transactions, choose payment methods and judge sellers with more confidence (Ng, 2012). Perceived AI personalisation reflects the relevance of the products and offers a consumer sees, which may be associated with purchase choices that require little further evaluation (Emini et al., 2025).

Hence:

H4: Digital literacy is positively associated with purchase decision-making.

H5: Perceived AI personalisation is positively associated with purchase decision-making.

The mediating role of perceived value

Following the extended S-O-R framework and the Value-based Adoption Model, perceived value is expected to carry part of the relationship between the two antecedents and the response. Hence:

H6: Perceived value mediates the relationship between digital literacy and purchase decision-making.

H7: Perceived value mediates the relationship between perceived AI personalisation and purchase decision-making.

Figure 1 presents the conceptual model

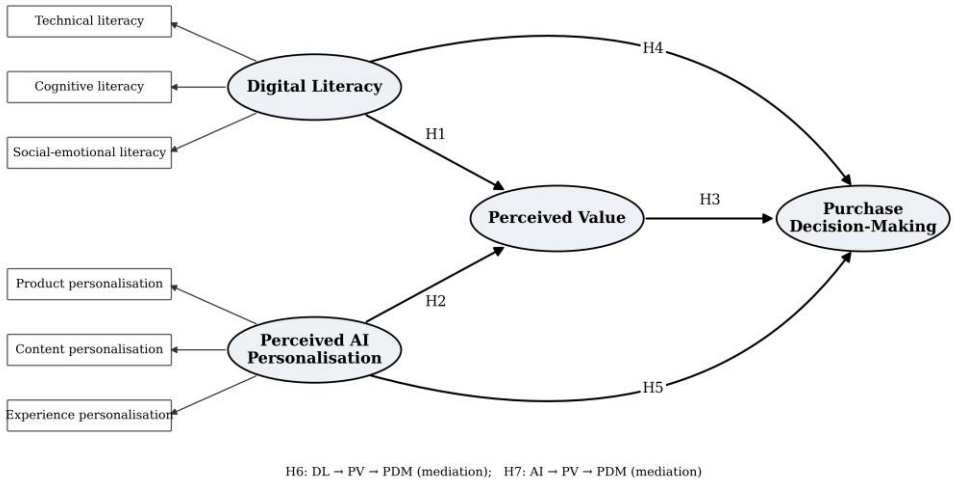


Figure 1. Conceptual model

Research Methodology

Research design and data collection

This study adopted a quantitative, cross-sectional survey design. Primary data were collected through a structured online questionnaire administered via Google Forms to women who use social commerce platforms, drawn mainly from Chennai, Puducherry and Kolkata.

Data screening and sample

A total of 178 responses were received. Response quality was screened for straight-lining, identified as responses with zero variation (a standard deviation of zero) across all 69 Likert-scale items of the wider questionnaire. Nine responses met this criterion. Because these items measure several distinct constructs, such patterns were treated as potentially inattentive responses and removed, as they can inflate construct correlations and reliability in PLS-SEM (Hair et al., 2017). Of the remaining 169 responses, 40 were from respondents who identified as male or did not state their gender, and these were excluded because the study focuses on women consumers. The final analytical sample therefore comprised 129 women. No values were missing. An a priori G*Power analysis (Faul et al., 2007) was conducted for the largest structural equation, in which purchase decision-making was predicted by three predictor constructs. Assuming $f^2 = 0.15$, $\alpha = 0.05$ and statistical power of 0.80, the analysis indicated a minimum sample of 77. The final sample of 129

therefore exceeded this minimum. This calculation was used as a minimum power check rather than as the sole justification for PLS-SEM sample adequacy.

Measures

All items used a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Digital literacy was operationalised using nine context-adapted items based on the three conceptual dimensions of Ng (2012); the items are not the original Ng scale but were written for the social commerce context. Perceived AI personalisation was operationalised using nine context-adapted items informed by the AI personalisation literature, including Emini et al. (2025), and organised into product, content and experience personalisation dimensions. Perceived value was measured with four items adapted from Zeithaml (1988) and Sweeney and Soutar (2001). Purchase decision-making was measured with six items, one for each purchase-choice dimension in Kotler and Keller (2018), with wording developed for social commerce. The Appendix lists all items with their sources. All 28 items were retained in the analysis.

Specification of purchase decision-making

Purchase decision-making was specified as a formative construct, operationalised through six distinct purchase-choice components: product, brand or seller, channel, quantity, timing and payment method. The specification follows the decision rules of Jarvis et al. (2003). First, the direction of causality runs from the indicators to the construct: the overall decision is defined by the choices a consumer makes, rather than the choices being outcomes of a common underlying tendency. Second, the indicators are not interchangeable: each covers a different part of the buying process, and dropping one would remove part of the construct's content. Third, the indicators need not covary: a consumer may, for example, be decisive about the seller but not about the quantity. Although each item is written as a behavioural statement, the items refer to different choices rather than to repeated expressions of the same tendency. Digital literacy, perceived AI personalisation and perceived value were specified as reflective.

Data analysis

The data were analysed with Partial Least Squares Structural Equation Modelling (PLS-SEM) using the seminr package (Ray et al., 2022) in R (R Core Team, 2025), following Hair et al. (2021). PLS-SEM was selected because the model combines reflective higher-order constructs with a formative endogenous construct and has an explicit predictive component (Hair et al., 2019). The analysis therefore focused on both measurement quality and the explanatory and predictive performance of the structural model. Digital literacy and perceived AI personalisation were estimated as reflective-reflective higher-order constructs using the two-stage approach (Sarstedt et al., 2019). The analysis assessed the reflective

and formative measurement models, then the structural model. Significance was tested with bootstrapping (10,000 subsamples) using percentile confidence intervals, mediation was assessed through specific indirect effects (Zhao et al., 2010), and predictive performance was assessed with PLSpredict (Shmueli et al., 2019).

Results

Respondent profile

Table 1 presents the profile of the 129 respondents. The sample was predominantly young (55.8% aged 18–25) and urban (92.2%), with 69.8% holding a master's or doctoral degree. Most respondents shopped through social commerce rarely (53.5%) or monthly (32.6%) and spent less than ₹3,000 per month (77.5%). Fashion and apparel (63.6%) and beauty and personal care (40.3%) were the most purchased categories, and Meesho (39.5%) was the most preferred named platform.

Table 1

Profile of respondents (n = 129)

Variable	Category	n	%
Age	18–25 years	72	55.8
	26–35 years	9	7.0
	36–45 years	33	25.6
	46–55 years	13	10.1
	Above 55 years	2	1.6
Education	Secondary/High school	1	0.8
	Bachelor's degree	37	28.7
	Master's degree	76	58.9
	Doctorate	14	10.9
	Others	1	0.8
Occupation	Student	45	34.9
	Employed (private)	49	38.0
	Employed (government)	6	4.7
	Self-employed	15	11.6
	Unemployed	8	6.2
	Others	6	4.7
Monthly income	Below ₹20,000	49	38.0
	₹20,001–40,000	31	24.0
	₹40,001–60,000	20	15.5
	₹60,001–80,000	7	5.4
	Above ₹80,000	22	17.1
Location	Urban	119	92.2
	Rural	10	7.8

Online shopping experience	Less than 1 year	13	10.1
	1–2 years	13	10.1
	3–5 years	50	38.8
	6–10 years	33	25.6
	More than 10 years	20	15.5
Social commerce experience	Less than 1 year	33	25.6
	1–2 years	30	23.3
	3–5 years	38	29.5
	6–10 years	18	14.0
	More than 10 years	10	7.8
Purchase frequency	Rarely	69	53.5
	Monthly	42	32.6
	Fortnightly	6	4.7
	Weekly	9	7.0
	More than once a week	3	2.3
Monthly spending on social commerce	Below ₹1,000	43	33.3
	₹1,001–3,000	57	44.2
	₹3,001–5,000	19	14.7
	₹5,001–10,000	8	6.2
	Above ₹10,000	2	1.6
Preferred social commerce platform(s)*	Meesho	51	39.5
	Instagram Shopping	35	27.1
	WhatsApp Business	12	9.3
	Shopsy	9	7.0
	Facebook Marketplace	8	6.2
	Others	62	48.1
Products purchased*	Fashion/apparel	82	63.6
	Beauty and personal care	52	40.3
	Home and lifestyle	44	34.1
	Groceries/FMCG	36	27.9

	Electronics	13	10.1
	Others	8	6.2

Note: * Multiple responses allowed; percentages exceed 100.

Preliminary checks

Although PLS-SEM does not require multivariate normality, item-level skewness and kurtosis were inspected and did not indicate extreme departures from normality. Common method bias was examined with two diagnostics. In Harman's single-factor test, a single unrotated factor accounted for 23.71% of the variance across the 28 items, and inner VIF values ranged from 1.124 to 1.273, below the 3.3 threshold suggested by Kock (2015). The diagnostics did not provide evidence of substantial common method bias under the criteria applied (Podsakoff et al., 2003).

Reflective measurement model

Table 2 reports the first-order reflective constructs. Most loadings exceeded 0.708, and two indicators loaded below this benchmark (DL5 = 0.701; DL9 = 0.579). The other first-order constructs showed composite reliability between 0.785 and 0.864 and AVE between 0.555 and 0.680. Cronbach's alpha for cognitive (0.648) and social-emotional literacy (0.597) was below 0.70, which is common for constructs with three items, as alpha tends to underestimate reliability (Hair et al., 2019). These measurement results should therefore be interpreted with caution. Technical literacy showed weaker measurement quality than the other lower-order dimensions (α = 0.504; CR = 0.661; AVE = 0.496). In particular, DL1 had a near-zero loading (−0.005), which warrants caution regarding the suitability of this adapted item in the social commerce context. A check of the raw data confirmed that DL1 was coded in the same direction and on the same scale as the other items, so the result does not reflect a coding error. DL1 correlated weakly with DL2 (r = 0.15) and DL3 (r = 0.08). Its wording refers to the use of several devices (smartphone, laptop and tablet), whereas DL2 and DL3 refer to operating social commerce platforms; DL1 may therefore capture access to multiple devices rather than platform skill. Because the study sought to preserve the conceptual coverage of Ng's (2012) framework, the item was retained for the reported analysis; this should be considered when interpreting the digital literacy findings.

Table 2

First-order reflective measurement model

Construct	**Item**	**Mean**	**SD**	**Loading**	**α**	**ϱA**	**CR**	**AVE**
Technical literacy	DL1	3.54	1.21	−0.005	0.504	0.609	0.661	0.496
	DL2	3.39	0.96	0.825				
	DL3	3.79	0.82	0.898				
Cognitive literacy	DL4	3.98	0.80	0.851	0.648	0.681	0.808	0.585
	DL5	3.59	0.82	0.701				

	DL6	4.03	0.77	0.735				
Social-emotional literacy	DL7	3.33	0.92	0.791	0.597	0.647	0.785	0.555
	DL8	3.88	0.73	0.838				
	DL9	3.72	0.97	0.579				
Product personalisation	AI1	3.79	0.75	0.870	0.727	0.746	0.846	0.647
	AI2	3.80	0.68	0.778				
	AI3	3.99	0.67	0.760				
Content personalisation	AI4	3.76	0.85	0.766	0.711	0.718	0.838	0.633
	AI5	3.78	0.70	0.828				
	AI6	3.58	0.77	0.792				
Experience personalisation	AI7	3.67	0.74	0.789	0.766	0.778	0.864	0.680
	AI8	3.67	0.74	0.836				
	AI9	3.74	0.80	0.848				
Perceived value	PV1	3.61	0.78	0.732	0.782	0.785	0.858	0.603
	PV2	3.63	0.71	0.826				
	PV3	3.47	0.81	0.802				
	PV4	3.49	0.79	0.741				

Note: α = Cronbach's alpha; ρA = rho_A; CR = composite reliability (ρc); AVE = average variance extracted. Initial items = 28; items deleted = 0; final items = 28 (22 reflective items in this table; 6 formative purchase decision-making items in Table 5).

Table 3 reports the higher-order constructs. Because the lower-order dimensions were treated as reflective dimensions of the higher-order constructs, the higher-order assessment focused on the reliability, convergent validity and size of the dimension loadings. The dimensions loaded strongly on digital literacy (0.753 to 0.876) and perceived AI personalisation (0.792 to 0.888). Both higher-order constructs met the reliability and convergent validity criteria (digital literacy: CR = 0.855, AVE = 0.663; perceived AI personalisation: CR = 0.870, AVE = 0.691).

Table 3

Higher-order construct assessment

Higher-order construct	Lower-order dimension	Loading	α	ρA	CR	AVE
Digital literacy	Technical literacy	0.809	0.745	0.762	0.855	0.663
	Cognitive literacy	0.876				
	Social-emotional literacy	0.753				
Perceived AI personalisation	Product personalisation	0.792	0.777	0.801	0.870	0.691
	Content personalisation	0.812				
	Experience personalisation	0.888				

Note: Estimated with the two-stage approach; lower-order construct scores serve as indicators of the higher-order constructs.

Table 4 reports discriminant validity among the reflective constructs. HTMT ratios between digital literacy, perceived AI personalisation and perceived value ranged from 0.378 to 0.504, well below 0.85 (Henseler et al., 2015). At the first-order level, the HTMT between technical and cognitive literacy was high (1.005). This indicates substantial empirical overlap between the two dimensions. Although they were theoretically specified as distinct dimensions of the higher-order construct, their empirical distinction is weak in this sample.

Table 4

Discriminant validity: HTMT ratios (reflective constructs)

Construct	DL	AI	PV
Digital literacy (DL)			
Perceived AI personalisation (AI)	0.444		
Perceived value (PV)	0.378	0.504	

Note: All values are below 0.85 (Henseler et al., 2015). HTMT is not applied to the formative purchase decision-making construct.

Formative measurement model

Table 5 reports the formative purchase decision-making construct. Indicator VIF values ranged from 1.200 to 1.572, indicating no collinearity concern. None of the six indicator weights was statistically significant. Following Hair et al. (2017), indicators with non-significant weights can be retained when their loadings are sufficiently high, because they may still contribute absolute importance to the construct. PD1, PD2, PD3, PD5 and PD6 had loadings above 0.50, although the confidence intervals of PD3, PD5 and PD6 included zero. PD4 had a lower loading of 0.406, and its confidence interval also included zero. It was nevertheless retained

because purchase quantity represents one of the six theoretically specified purchase-choice components.

Convergent validity of the formative purchase decision-making construct could not be assessed through redundancy analysis because a separate global measure of purchase decision-making was not included in the questionnaire. This is a limitation of the measurement model and should be considered when interpreting the formative construct.

Table 5

Formative measurement model: purchase decision-making

Indicator (purchase choice)	Weight	t	95% CI (weight)	Loading	95% CI (loading)	VIF
PD1 (product)	0.322	1.664	[−0.150, 0.626]	0.617	[0.064, 0.811]	1.237
PD2 (brand/seller)	0.327	1.487	[−0.198, 0.659]	0.658	[0.060, 0.836]	1.284
PD3 (channel)	0.380	1.505	[−0.279, 0.761]	0.678	[−0.192, 0.900]	1.285
PD4 (quantity)	0.139	0.936	[−0.148, 0.440]	0.406	[−0.054, 0.660]	1.200
PD5 (timing)	0.196	0.993	[−0.212, 0.579]	0.570	[−0.090, 0.828]	1.481
PD6 (payment)	0.256	0.976	[−0.361, 0.696]	0.626	[−0.145, 0.902]	1.572

Note: Bootstrapping with 10,000 subsamples; percentile confidence intervals. Indicators with loadings of 0.50 or higher retained following Hair et al. (2017); PD4 retained for content coverage. Redundancy analysis not possible (no global item).

4.5 Structural model

Table 6 reports collinearity, explanatory power and effect sizes. Inner VIF values ranged from 1.124 to 1.273. The model explained 19.4% of the variance in perceived value and 36.5% in purchase decision-making. Perceived AI personalisation had a medium effect size on purchase decision-making ($f^2 = 0.198$) and a small effect size on perceived value ($f^2 = 0.132$). Digital literacy had a small effect size on perceived value ($f^2 = 0.036$) and a negligible one on purchase decision-making ($f^2 = 0.009$), and perceived value had a small effect size on purchase decision-making ($f^2 = 0.020$). Table 7 reports the PLSpredict results (10 folds, 10 repetitions) for the second-stage model. All Q^2predict values were positive (0.009 to 0.123), indicating predictive relevance. PLS-SEM produced lower RMSE values than the linear benchmark for nine of the ten indicators, although PD2 showed a slightly higher prediction error. Overall, the results indicate predictive relevance, with PLS-SEM producing lower prediction errors than the linear benchmark for nine of the ten indicators (Shmueli et al., 2019).

Table 6

Collinearity, explanatory power and effect sizes

Path	VIF	f^2	Effect size
DL → PV	1.124	0.036	Small
AI → PV	1.124	0.132	Small
DL → PDM	1.164	0.009	Negligible
AI → PDM	1.273	0.198	Medium
PV → PDM	1.241	0.020	Small

R^2 (adjusted R^2): perceived value = 0.194 (0.181); purchase decision-making = 0.365 (0.349).

Note: DL = digital literacy; AI = perceived AI personalisation; PV = perceived value; PDM = purchase decision-making. f^2 thresholds: 0.02 small, 0.15 medium, 0.35 large (Cohen, 1988).

Table 7

Predictive assessment (PLSpredict, 10 folds, 10 repetitions)

Indicator	Q^2predict	RMSE (PLS-SEM)	RMSE (LM)	PLS < LM
PV1	0.046	0.762	0.795	Yes
PV2	0.009	0.702	0.711	Yes
PV3	0.101	0.766	0.800	Yes
PV4	0.059	0.765	0.792	Yes
PD1	0.071	0.715	0.798	Yes
PD2	0.100	0.764	0.751	No
PD3	0.123	0.837	0.860	Yes
PD4	0.018	0.614	0.662	Yes
PD5	0.042	0.705	0.707	Yes
PD6	0.058	0.694	0.703	Yes

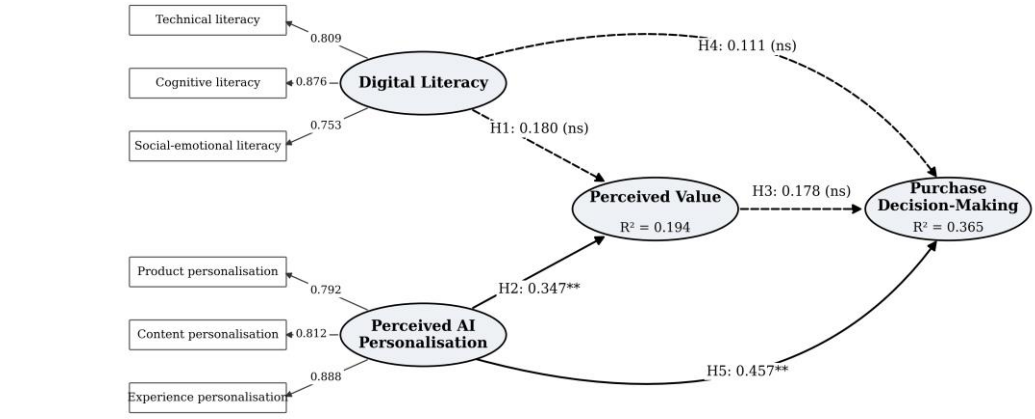
Note: Out-of-sample values from the second-stage model. LM = linear regression benchmark (Shmueli et al., 2019). Positive Q^2predict indicates predictive relevance.

Table 8 and Figure 2 present the hypothesis tests. Perceived AI personalisation was positively associated with perceived value ($\beta = 0.347$, $t = 3.690$, $p < 0.001$) and with purchase decision-making ($\beta = 0.457$, $t = 3.123$, $p = 0.002$), supporting H2 and H5. Digital literacy was not significantly associated with perceived value ($\beta = 0.180$, $t = 1.728$, $p = 0.084$) or purchase decision-making ($\beta = 0.111$, $t = 0.571$, $p = 0.568$), so H1 and H4 were not supported. Perceived value was not significantly associated with purchase decision-making ($\beta = 0.178$, $t = 0.840$, $p = 0.401$), so H3 was not supported. Perceived AI personalisation had the largest direct path coefficient among the relationships tested.

Table 8
Hypothesis testing: direct effects

H	Path	β	SD	t	p	95% CI	Decision
H1	DL → PV	0.180	0.104	1.728	0.084	[−0.018, 0.388]	Not supported
H2	AI → PV	0.347	0.094	3.690	<0.001	[0.160, 0.526]	Supported
H3	PV → PDM	0.178	0.212	0.840	0.401	[−0.330, 0.546]	Not supported
H4	DL → PDM	0.111	0.194	0.571	0.568	[−0.306, 0.508]	Not supported
H5	AI → PDM	0.457	0.146	3.123	0.002	[0.089, 0.667]	Supported

Note: Bootstrapping with 10,000 subsamples. p-values are two-tailed and derived from the bootstrap t-values; 95% CIs are percentile intervals. A path is supported when $p < 0.05$ and the CI excludes zero.



Note: ** p < 0.01; * p < 0.05; ns = not significant (dashed lines). Standardised path coefficients; bootstrapping with 10,000 subsamples; n = 129. Purchase decision-making is formative (6 ind
Indirect effects H6 (DL → PV → PDM) and H7 (AI → PV → PDM) were not significant.

Figure 2. Structural model results

Mediation analysis

Table 9 reports the specific indirect and total effects. The indirect effect of digital literacy on purchase decision-making through perceived value was not significant (β = 0.032, 95% CI [−0.053, 0.137]), and neither was the indirect effect of perceived AI personalisation (β = 0.062, 95% CI [−0.115, 0.214]). H6 and H7 were therefore not supported. Following Zhao et al. (2010), the perceived AI personalisation pattern is direct-only non-mediation, because its direct effect was significant, while the digital literacy pattern is no-effect non-mediation, because neither its direct nor its indirect effect was significant. The total effect of perceived AI personalisation on purchase decision-making was significant (β = 0.519, t = 3.761, p < 0.001, 95% CI [0.124, 0.688]), while that of digital literacy was not (β = 0.143, t = 0.819, p = 0.413, 95% CI [−0.221, 0.499]).

Table 9
Mediation analysis: specific indirect and total effects

H	Indirect path	β	SD	t	p	95% CI	Mediation type	Decision
H6	DL → PV → PDM	0.032	0.047	0.687	0.492	[−0.053, 0.137]	No-effect non-mediation	Not supported
H7	AI → PV → PDM	0.062	0.080	0.771	0.441	[−0.115, 0.214]	Direct-only non-mediation	Not supported

Total effects on purchase decision-making: DL = 0.143 (t = 0.819, p = 0.413, 95% CI [−0.221, 0.499]); AI = 0.519 (t = 3.761, p < 0.001, 95% CI [0.124, 0.688]).
Note: p-values are two-tailed and derived from the bootstrap t-values; 95% CIs are percentile intervals. Mediation type follows Zhao et al. (2010).

Robustness check: alternative reflective specification of purchase decision-making

As a sensitivity analysis, the structural model was re-estimated by treating purchase decision-making as a reflective construct. Under this specification, PD1, PD3 and PD4 were removed to achieve acceptable convergent validity, leaving PD2, PD5 and PD6 (CR = 0.806; AVE = 0.585). The relationship between perceived AI personalisation and purchase decision-making remained positive and significant (β = 0.402, t = 3.787, p < 0.001), while the relationship between perceived value and purchase decision-making remained non-significant (β = −0.060, t = −0.617, p = 0.537). Digital literacy was significant under the reduced reflective specification (β = 0.276, t = 2.556, p = 0.011), whereas it was non-significant in the main formative specification (β = 0.111, t = 0.571, p = 0.568). These results indicate that the estimated relationship between digital literacy and purchase decision-making depends partly on the operationalisation of the outcome construct. The formative specification is retained as the primary model because the six indicators were designed to represent distinct purchase-choice components.

Discussion

This study examined how digital literacy and perceived AI personalisation relate to the purchase decision-making of women social commerce users, and whether perceived value carries these relationships. Two of the seven hypotheses were supported. Perceived AI personalisation was positively associated with perceived value, but the proposed perceived value pathway to purchase decision-making was not supported. Perceived AI personalisation showed a positive direct association with purchase decision-making (β = 0.457) and with perceived value (β = 0.347). This is consistent with Emini et al. (2025), who linked AI-driven personalisation with engagement in social commerce, and with Guo and Li (2022), who linked social commerce features with perceived value. Among the women

surveyed, higher perceived AI personalisation was associated with higher perceived value and higher purchase decision-making. Digital literacy was not significantly associated with perceived value or purchase decision-making, although its relationship with perceived value was positive but not significant ($p = 0.084$). One possible explanation is the nature of the sample: most respondents were young, urban and held postgraduate degrees, so the variation in digital skills may have been too narrow to show a clear relationship. The weak measurement of technical literacy (Section 4.3) may also have reduced the precision of this construct. In addition, the sensitivity analysis in Section 4.7 indicates that the digital literacy relationship depends partly on how purchase decision-making is operationalised. Perceived value was not significantly associated with purchase decision-making and did not mediate either relationship. This differs from the Value-based Adoption Model (Kim et al., 2007) and from studies that link value to purchase intention in social commerce (Guo & Li, 2022; Wang & Shahzad, 2024). One possible explanation is the relatively low purchase intensity of the sample: 77.5% reported monthly social commerce spending below ₹3,000 and 53.5% reported purchasing rarely. In such settings, purchase choices may depend on factors other than perceived value, such as convenience, trust or social influence (Hajli et al., 2017; Hu et al., 2019). These mechanisms were not tested in the present study and therefore require future empirical examination. Taken together, the findings provide a context-specific qualification of the proposed value pathway. Perceived AI personalisation showed a significant direct association with purchase decision-making, whereas the proposed perceived value mediation pathway was not supported.

Implications

Theoretical implications

The study applies an extended S-O-R framework, with an individual-level antecedent and a platform-related stimulus, together with the Value-based Adoption Model, to women social commerce users in India. The organism stage (perceived value) did not transmit the relationships in this sample, which suggests that value-based models may need qualification in low-spend, socially embedded shopping contexts. The study also operationalises purchase decision-making formatively through six distinct purchase choices, which differs from the common use of reflective purchase intention measures, and the sensitivity analysis shows that conclusions about digital literacy depend partly on this choice of operationalisation.

Practical implications

The positive association between perceived AI personalisation and purchase decision-making suggests that platform providers could examine the relevance and quality of personalised recommendations and content for women users. Experience personalisation showed the highest loading (0.888) on perceived AI personalisation;

this is a descriptive result indicating a close association with the overall construct and does not show that this dimension has the largest relationship with purchase decision-making. Since perceived value was not associated with purchase decision-making in this sample, platforms may also consider how easily women can move from a relevant recommendation to completing a purchase.

Relevance to Viksit Bharat@2047

Viksit Bharat@2047 is treated in this study as the policy context within which digital inclusion and women's participation in digital commerce are discussed, rather than as an outcome directly tested by the model. The study did not measure women's income, employment or wider economic participation, so it cannot show a contribution to national development. Within this context, the findings show that, among the women surveyed, perceived AI personalisation was associated with purchase decision-making in social commerce. The absence of a clear association for digital literacy in this relatively skilled, urban sample suggests that its role should be examined among women with more varied levels of digital experience.

Limitations and Future Research

The study has several limitations. First, the sample of 129 women was drawn by convenience from selected Indian locations and was mainly young, urban and postgraduate-educated, so the findings apply to women social commerce users similar to those in the sample and should not be generalised to Indian women consumers as a whole. Second, the cross-sectional, self-reported design does not establish causality, and the relationships reported here are associations. Third, the convergent validity of the formative purchase decision-making construct could not be assessed through redundancy analysis because no global measure of purchase decision-making was included; none of its indicator weights was significant, and PD4 had a relatively low loading of 0.406, with a confidence interval that included zero. Future studies should include a global single-item measure to allow redundancy analysis. Fourth, all items were retained to preserve content coverage; as a result, DL1 had a near-zero loading, the technical literacy dimension did not meet the usual reliability and convergent validity thresholds (CR = 0.661; AVE = 0.496), and it overlapped strongly with cognitive literacy. Future studies should refine the technical literacy items, for example by separating device access from platform skill. Fifth, the perceived AI personalisation scale was context-adapted, and its three-dimensional structure should be validated in other samples. Sixth, future research could examine trust, impulse buying tendency or social influence as alternative mechanisms, compare women and men through multi-group analysis, and test whether perceived value relates to satisfaction and repurchase rather than to purchase choices.

II. CONCLUSION

This study examined how digital literacy and perceived AI personalisation relate to the purchase decision-making of women social commerce users, with perceived value as a proposed mediator. PLS-SEM results from 129 women show that perceived AI personalisation was positively associated with both perceived value and purchase decision-making, while digital literacy showed no significant association with either in the main model. Perceived value was not associated with purchase decision-making and did not mediate these relationships. The findings indicate that perceived AI personalisation was positively associated with purchase decision-making among the women surveyed, while perceived value did not provide the expected mediating pathway. They provide consumer-level evidence relevant to discussions of digital inclusion under Viksit Bharat@2047.

III. REFERENCES

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Appendix A: Measurement Items

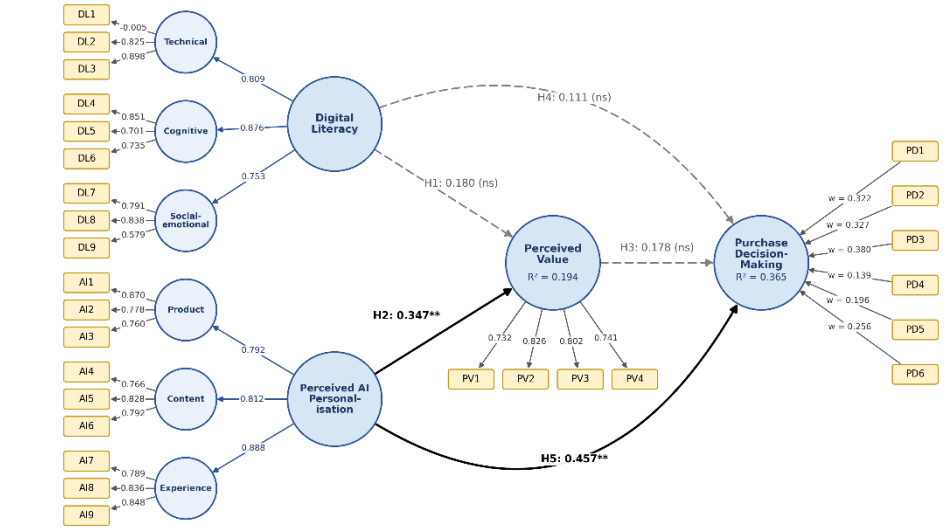
Construct	Code	Item	Source/adaptation
Digital literacy	DL1	Technical: I can competently use various digital devices (smartphone, laptop, tablet) to shop on social commerce platforms.	Context-adapted from the conceptual dimensions of Ng (2012)
	DL2	Technical: I am able to troubleshoot basic technical problems while using social commerce apps or websites.	
	DL3	Technical: I know how to navigate the different features of social commerce platforms with ease.	
	DL4	Cognitive: I can effectively search for and evaluate product information on social commerce platforms.	
	DL5	Cognitive: I am able to critically assess the credibility of information shared by sellers online.	
	DL6	Cognitive: I can compare product options across different social commerce platforms before deciding.	
	DL7	Social-emotional: I feel comfortable communicating and interacting with sellers or other users on social commerce platforms.	

Construct	Code	Item	Source/adaptation
	DL8	Social-emotional: I understand the appropriate online etiquette when engaging in social commerce transactions.	
	DL9	Social-emotional: I am confident in protecting my personal information and privacy while shopping on social commerce platforms.	
Perceived AI personalisation	AI1	Product: The platform recommends products that match my preferences.	Context-adapted; informed by Emini et al. (2025)
	AI2	Product: Product suggestions I receive are relevant to my needs.	
	AI3	Product: The platform adapts product recommendations based on my past behaviour.	
	AI4	Content: The content (ads, posts, offers) shown to me is customised to my interests.	
	AI5	Content: I receive personalised promotions or discounts based on my shopping history.	
	AI6	Content: The information displayed feels tailored specifically for me.	
	AI7	Experience: My overall browsing experience feels customised to my preferences.	
	AI8	Experience: The platform's interface adjusts based on my usage patterns.	
	AI9	Experience: I feel the platform understands my individual shopping habits.	
Perceived value	PV1	This social commerce platform offers good value for the money I spend.	Adapted from Zeithaml (1988); Sweeney & Soutar (2001)
	PV2	The benefits I get from this social commerce platform justify the costs.	
	PV3	Using this social commerce platform is a worthwhile investment of my time/money.	

Construct	Code	Item	Source/adaptation
	PV4	This social commerce platform offers high value compared to alternatives.	
Purchase decision-making (formative)	PD1	I choose to purchase a specific product after browsing it on the social commerce platform.	Adapted from the purchase-choice dimensions in Kotler & Keller (2018); wording developed for social commerce
	PD2	I select a particular brand or seller because of the information available on the platform.	
	PD3	I decide to complete my purchase through this social commerce platform rather than another channel.	
	PD4	I decide on the quantity of the product to purchase based on my needs and the information provided.	
	PD5	I decide on the right time to make my purchase based on offers, reviews, or recommendations on the platform.	
	PD6	I choose a payment method that I find convenient and trustworthy on the platform.	

Note: All 28 items were retained in the analysis. Items were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Appendix B: Full Estimated PLS-SEM Model



Note: Rectangles = indicators; circles = constructs (small circles = dimensions of higher-order constructs). Values on reflective indicator arrows are outer loadings; w = formative weights of purchase decision-making. Path values are standardised coefficients (bootstrapping, 10,000 subsamples). ** $p < 0.01$; * $p < 0.05$; ns = not significant (dashed). Indirect effects H6 and H7 not significant. n = 129.

Figure B1. Full estimated model with indicator loadings and weights, path coefficients and R^2 (seminr output, n = 129)