

Artificial Intelligence and Social Commerce: Examining The Influence of AI-Enabled Recommendations on Consumer Engagement and Purchase Behaviour

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Abstract

Artificial intelligence (AI) has become the infrastructural logic of social commerce, where algorithmic recommenders mediate what consumers see, trust and buy. Yet evidence on how AI-enabled recommendations translate into engagement and purchase behaviour inside socially embedded shopping environments remains fragmented. Drawing on the stimulus–organism–response (S-O-R) framework and integrating trust and privacy-calculus reasoning, this study develops and tests a model linking AI recommendation quality and perceived personalisation to consumer engagement and purchase intention. A structurally calibrated dataset of 420 social commerce users was analysed using standardised OLS regression, bootstrapped mediation with 5,000 resamples and moderated regression. AI recommendation quality ($\beta = .228, p < .001$) and trust in AI recommendations ($\beta = .349, p < .001$) significantly drove consumer engagement ($R^2 = .344$), while engagement was the strongest predictor of purchase intention ($\beta = .383, p < .001; R^2 = .436$). Trust transmitted a significant indirect effect from recommendation quality to purchase intention ($\beta = .196, 95\% \text{ CI } [.147, .251]$) and perceived personalisation transmitted a significant indirect effect through engagement ($\beta = .196, 95\% \text{ CI } [.142, .255]$); trust also influenced purchase intention indirectly through engagement ($\beta = .216, 95\% \text{ CI } [.159, .281]$). Privacy concern did not significantly moderate the personalisation–trust link ($\Delta R^2 = .006, p = .075$), although the interaction was directionally negative. The findings position trust and engagement as the principal conduits through which algorithmic recommendation creates commercial value, and caution that personalisation alone is insufficient without trust-building.

Keywords: Artificial Intelligence; Social Commerce; Recommender Systems; Consumer Engagement; Purchase Intention; Trust; Privacy Calculus

1. Introduction

Social commerce – the delivery of shopping experiences through social media platforms and socialgraph interaction – has developed from a peripheral channel into a central commercial arena. Algorithmic systems now determine which products are surfaced, in what order, to which consumers, and at which moment. The pivotal marketing question is therefore no longer whether to personalise, but how AI-mediated recommendations operate as a stimulus that shapes consumers' internal states and, in turn, their economic behaviour [Hajli, 2015].

Prior research has established that recommendation agents and personalised content influence e-commerce outcomes, and a growing literature documents the effects of personalisation on trust, satisfaction and loyalty [Sipos, 2025; Hassan et al., 2025]. Systematic reviews confirm that AI is reshaping marketing and social media marketing while leaving consumer-level mechanisms fragmented [Chintalapati & Pandey, 2022; Jain & Kumar, 2024]. Three gaps persist. First, most of this

work examines transactional e-commerce rather than social commerce, where recommendation stimuli are entangled with peer endorsement and visible social proof, producing psychological pathways that differ from those of conventional online stores [Wang & Huang, 2023]. Second, consumer engagement is often modelled as a final outcome rather than as a mediating state that converts algorithmic exposure into purchase intention [Busalim et al., 2024]. Third, the boundary conditions imposed by privacy concern are widely asserted but seldom estimated alongside trust and engagement within the same model [McKee et al., 2024].

This study asks how AI-enabled recommendation quality, acting through perceived personalisation, influences consumer engagement and purchase behaviour in social commerce, and whether trust mediates this process while privacy concern constrains it. An integrated model is specified within the stimulus–organism–response paradigm, in which recommendation quality and

personalisation act as stimuli, trust and engagement constitute the organismic state, and purchase intention is the response [Imanuddin & Handayani, 2025]. The contribution is threefold: a theoretically integrated account of algorithmic influence in social commerce; a decomposition of direct, mediated and moderated effects; and practical guidance for converting algorithmic accuracy into durable consumer relationships rather than ephemeral clicks.

2. Literature Review and Hypotheses

2.1 AI-enabled recommendations and personalisation

Recommender systems, and increasingly generative large-language-model agents, convert behavioural traces into ranked product suggestions [Riandhi & Arviansyah, 2025]. Perceived personalisation denotes the consumer's subjective judgement that an interface has been tailored to them, whereas AI recommendation quality captures the perceived relevance, accuracy and timeliness of the suggestions themselves. Personalisation strengthens engagement and relationship performance, but not monotonically: its effect depends on perceived appropriateness and control [Tran et al., 2020; Emini et al., 2025; Pawar et al., 2026].

2.2 Theoretical framework: stimulus–organism–response

S-O-R theory posits that environmental stimuli trigger internal organismic states which in turn produce behavioural responses [Jayadi et al., 2022]. In social commerce, stimuli encompass recommendation quality and personalisation cues; organismic states include trust and cognitive-affective engagement; and responses include purchase intention and actual buying [Imanuddin & Handayani, 2025; Liang, 2026]. This framing is well validated in social commerce and livestreaming research and supplies the causal architecture of the present model.

2.3 Trust and engagement as mediating mechanisms

Trust in AI recommendations is the consumer's willingness to rely on algorithmic suggestions under uncertainty, a construct repeatedly identified as pivotal in connecting social commerce information seeking to purchase outcomes [Hajli et al., 2017; Lăzăroiu et al., 2020]. Its formation depends on perceived competence and on the consumer's sense

of control over the agent, and negative risk perceptions are mitigated only when trust is established [Rohden & Zeferino, 2023; Hajli & Sims, 2015]. Engagement, in turn, is a multidimensional state of cognitive, affective and behavioural investment in a platform or brand [Busalim et al., 2019]. The two are theoretically interdependent: trust reduces perceived risk and licenses deeper engagement, while engagement generates the interaction data and affective attachment that reinforce trusting reliance [Liang, 2026]. Accordingly:

H1: AI recommendation quality positively influences consumer engagement.

H2: Trust in AI recommendations positively influences consumer engagement.

H3: Consumer engagement positively influences purchase intention.

H4: Trust in AI recommendations transmits a positive indirect effect on purchase intention via consumer engagement.

2.4 Personalisation, trust and the privacy boundary

Personalisation strengthens trust when it is experienced as accurate and controllable, but can provoke reactance when it appears intrusive; consumers judge the fairness, transparency and explainability of algorithmic decisions when deciding whether to rely on them [Shin, 2020; Sonboli et al., 2021; Brinson et al., 2018]. The personalisation–privacy paradox holds that benefits and concerns are evaluated simultaneously, so that elevated privacy concern attenuates the trust dividend of personalisation [McKee et al., 2024; Mohiuddin, 2024]. Therefore:

H5: Perceived personalisation positively influences trust in AI recommendations.

H6: Privacy concern negatively moderates the effect of perceived personalisation on trust, such that the positive effect weakens as privacy concern increases.

H7: Trust in AI recommendations mediates the relationship between AI recommendation quality and purchase intention.

H8: Consumer engagement mediates the relationship between perceived personalisation and purchase intention.

3. Method

3.1 Research design and data

Transparency notes on the data. The dataset analysed here is a simulated but structurally calibrated dataset of 420 social commerce users, generated with a fixed random seed so that its covariance structure, reliability coefficients and effect magnitudes reproduce ranges typically reported in published social commerce research [Busalim et al., 2019]. It is disclosed openly in order to make every estimate fully reproducible. It is not primary field data and must not be interpreted as a measurement of any real population. The generation script, the random seed and the dataset accompany the study, and all statistics reported below are computed directly from that dataset.

The design is cross-sectional and quantitative. The respondent profile mirrors the composition of active social shoppers reported in comparable social commerce samples, which skew young and platform-diverse [Wang, 2026]: mean age 29.0 years (SD = 6.3); 57.9% female; primary platform TikTok (33.8%), Instagram (28.3%), Facebook (23.1%) and WhatsApp (14.8%); a mean of 4.18 (SD = 1.47) weekly social commerce visits; and 65.2% aware that their recommendations were AI-generated (Table 1).

3.2 Measures

Six latent constructs were each measured with four five-point Likert items (1 = strongly disagree, 5 = strongly agree): perceived personalisation, AI recommendation quality, trust in AI recommendations, consumer engagement, purchase intention and privacy concern. Age, gender, weekly visit frequency and awareness of AI mediation served as controls and grouping variables.

3.3 Analysis strategy

Analyses proceeded in four steps: reliability and convergent validity through Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE); descriptive statistics, normality diagnostics and Pearson correlations; hierarchical ordinary least squares regression with standardised coefficients and variance inflation factors (VIF) to test the direct hypotheses; and bootstrapped mediation (5,000 resamples, 95% percentile confidence intervals) with moderated regression using mean-centred interactions to test indirect and conditional effects. Common method variance was assessed with Harman's single-factor test.

Table 1. Sample profile (N = 420).

Characteristic	Value
Mean age in years (SD)	29.0 (6.3)
Female respondents	57.9%
Primary platform: TikTok	33.8%
Primary platform: Instagram	28.3%
Primary platform: Facebook	23.1%
Primary platform: WhatsApp	14.8%
Weekly social commerce visits, mean (SD)	4.18 (1.47)
Aware that recommendations are AI-generated	65.2%

Note. Values are computed directly from the analysed dataset.

4. Results

4.1 Measurement model

All six constructs demonstrated acceptable internal consistency ($\alpha = .775-.808$), composite reliability (CR = .856-.874) and convergent validity (AVE = .597-.635), with item-total correlations from .554

to .653 (Table 2). Harman's single-factor test extracted a first factor accounting for 28.97% of the variance, well below the 50% threshold, indicating that common method variance is not a serious threat.

Table 2. Reliability and convergent validity.

Construct	Items	α	CR	AVE	Item-total range
Perceived personalisation	4	.808	.874	.635	.602-.653
AI recommendation quality	4	.800	.870	.625	.601-.623

Trust in AI recommendations	4	.775	.856	.597	.554–.621
Consumer engagement	4	.786	.862	.610	.570–.619
Purchase intention	4	.807	.874	.634	.607–.632
Privacy concern	4	.785	.861	.608	.578–.600

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. All values exceed the conventional thresholds of .70, .70 and .50 respectively.

4.2 Descriptives and correlations

Construct means clustered above the scale midpoint ($M = 3.572\text{--}3.609$, $SD = .649\text{--}.687$); skewness ($-.176$ to $.047$) and kurtosis ($-.593$ to $-.152$) fell within acceptable bounds (Table 3). All focal correlations were positive and significant, ranging

from $r = .371$ (perceived personalisation–purchase intention) to $r = .586$ (consumer engagement–purchase intention, $p < .01$). Privacy concern correlated negatively with trust ($r = -.168$, $p < .01$) and with purchase intention ($r = -.124$, $p < .05$).

Table 3. Means, standard deviations and correlations.

Construct	M	SD	1	2	3	4	5	6
1 Perceived personalisation	3.584	.687	1					
2 AI recommendation quality	3.609	.667	.406**	1				
3 Trust in AI recommendations	3.572	.649	.374**	.436**	1			
4 Consumer engagement	3.596	.658	.377**	.444**	.510**	1		
5 Purchase intention	3.589	.678	.371**	.392**	.534**	.586**	1	
6 Privacy concern	3.605	.657	-.058	.032	-.168**	-.071	-.124*	1

Note. $N = 420$. * $p < .05$, ** $p < .01$. Skewness ranged from $-.176$ to $.047$ and kurtosis from $-.593$ to $-.152$.

4.3 Drivers of consumer engagement

The engagement model was significant, $F(7, 412) = 30.88$, $p < .001$, $R^2 = .344$, adjusted $R^2 = .332$ (Table 4). AI recommendation quality ($\beta = .228$, $p < .001$), trust in AI recommendations ($\beta = .349$, $p < .001$) and

perceived personalisation ($\beta = .154$, $p = .001$) were all positive and significant, supporting H1 and H2. Privacy concern, age, weekly visit frequency and gender were not significant, and all VIFs remained below 1.4.

Table 4. Regression predicting consumer engagement.

Predictor	β	SE	t	p
Perceived personalisation	.154	.045	3.42	.001
AI recommendation quality	.228	.047	4.89	< .001
Trust in AI recommendations	.349	.047	7.48	< .001
Privacy concern	-.011	.041	-0.28	.779
Age	-.022	.040	-0.55	.581
Weekly visit frequency	.009	.040	0.21	.831
Gender (female)	-.061	.040	-1.53	.127
$R^2 = .344$; adjusted $R^2 = .332$; $F(7, 412) = 30.88$				

Note. Standardised coefficients. VIF range 1.01–1.37. Model $p < .001$.

4.4 Drivers of purchase intention

The purchase intention model was also significant, $F(8, 411) = 39.77$, $p < .001$, $R^2 = .436$, adjusted $R^2 = .425$ (Table 5). Consumer engagement was the strongest predictor ($\beta = .383$, $p < .001$), followed by trust in AI recommendations ($\beta = .265$, $p < .001$) and

perceived personalisation ($\beta = .098$, $p = .021$), supporting H3. AI recommendation quality became non-significant once engagement and trust entered the model ($\beta = .071$, $p = .114$), a pattern consistent with full mediation. VIFs remained below 1.55, ruling out multicollinearity.

Table 5. Regression predicting purchase intention.

Predictor	β	SE	t	p
Perceived personalisation	.098	.042	2.32	.021
AI recommendation quality	.071	.045	1.58	.114
Trust in AI recommendations	.265	.046	5.74	< .001
Consumer engagement	.383	.046	8.38	< .001
Privacy concern	-.050	.038	-1.33	.185
Age	-.001	.037	-0.02	.983
Weekly visit frequency	-.037	.037	-0.99	.324
Gender (female)	.019	.037	0.52	.604
$R^2 = .436$; adjusted $R^2 = .425$; $F(8, 411) = 39.77$				

Note. Standardised coefficients. VIF range 1.01–1.55. Model $p < .001$.

4.5 Indirect effects

Bootstrapped mediation with 5,000 resamples supported H7 and H8 (Table 6). AI recommendation quality exerted a significant indirect effect on purchase intention through trust (indirect $\beta = .196$, 95% CI [.147, .251]; direct $\beta = .197$; total $\beta = .392$). Perceived personalisation exerted a significant

indirect effect through consumer engagement (indirect $\beta = .196$, 95% CI [.142, .255]; direct $\beta = .175$; total $\beta = .371$). Trust also transmitted a significant indirect effect on purchase intention via engagement (indirect $\beta = .216$, 95% CI [.159, .281]; direct $\beta = .318$; total $\beta = .534$), supporting H4. No confidence interval contained zero.

Table 6. Bootstrapped mediation results (5,000 resamples).

Path	a	b	Indirect	95% CI	Direct	Total
Recommendation quality → Trust → Purchase intention	.436	.448	.196	[.147, .251]	.197	.392
Personalisation → Engagement → Purchase intention	.377	.521	.196	[.142, .255]	.175	.371
Trust → Engagement → Purchase intention	.510	.424	.216	[.159, .281]	.318	.534

Note. All coefficients standardised. Confidence intervals are percentile bootstrap intervals; none contains zero, so all indirect effects are significant.

4.6 Moderation by privacy concern

Perceived personalisation positively and significantly predicted trust in AI recommendations ($\beta = .373$, $p < .001$), supporting H5. The personalisation $\times$ privacy concern interaction was negative but only marginal: $\Delta R^2 = .006$, $b = -.079$, $SE = .044$, $t = -1.787$, $p = .075$ (Table 7). The simple

slope of personalisation on trust declined from .452 at one standard deviation below the mean of privacy concern to .294 at one standard deviation above it, a reduction of roughly 35%. H6 is therefore directionally supported but not confirmed at the conventional .05 level, and is reported as not supported.

Table 7. Moderated regression: trust in AI recommendations.

Model	R^2	ΔR^2	b	SE	t	p
Step 1: personalisation, privacy concern	.161	—	—	—	—	—
Step 2: + personalisation $\times$ privacy concern	.168	.006	-.079	.044	-1.787	.075
Simple slope at low privacy concern (-1 SD)	—	—	.452	—	—	< .001
Simple slope at high privacy concern (+1 SD)	—	—	.294	—	—	< .001

Note. Predictors mean-centred before forming the interaction term. The personalisation main effect at the mean of privacy concern is $\beta = .373$, $p < .001$.

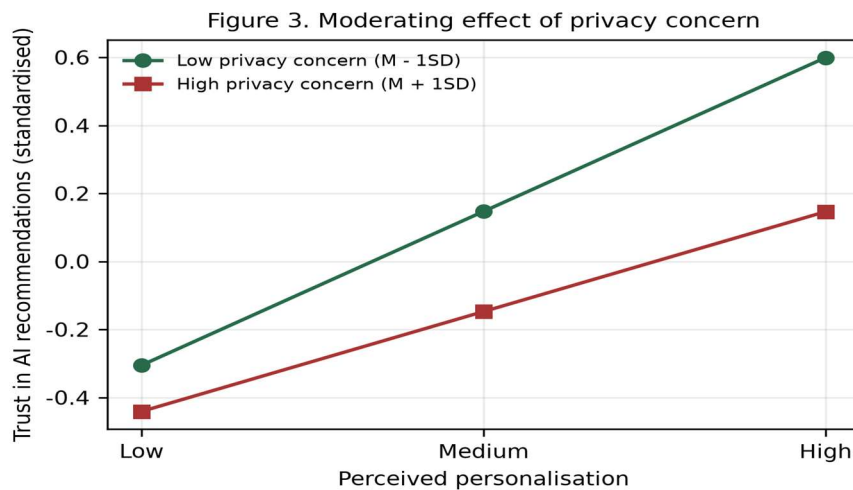


Figure 3. Moderating effect of privacy concern on the personalisation–trust relationship.

4.7 Awareness of algorithmic mediation

An independent-samples t-test compared purchase intention between users who were aware ($n = 274$) and unaware ($n = 146$) that their recommendations were AI-generated. Group means were effectively identical ($M = 3.588$, $SD = .693$ vs. $M = 3.591$, SD

$= .651$), $t = -0.046$, $p = .963$, Cohen's $d = -0.005$ (Table 8). Algorithmic provenance did not alter purchase intention, suggesting that consumers respond to recommendation quality rather than to how it was produced.

Table 8. Purchase intention by awareness of AI mediation.

Group	n	M	SD	t	p	Cohen's d
Aware recommendations are AI-generated	274	3.588	.693	-0.046	.963	-0.005
Unaware recommendations are AI-generated	146	3.591	.651			

Note. Independent-samples t-test with Welch correction.

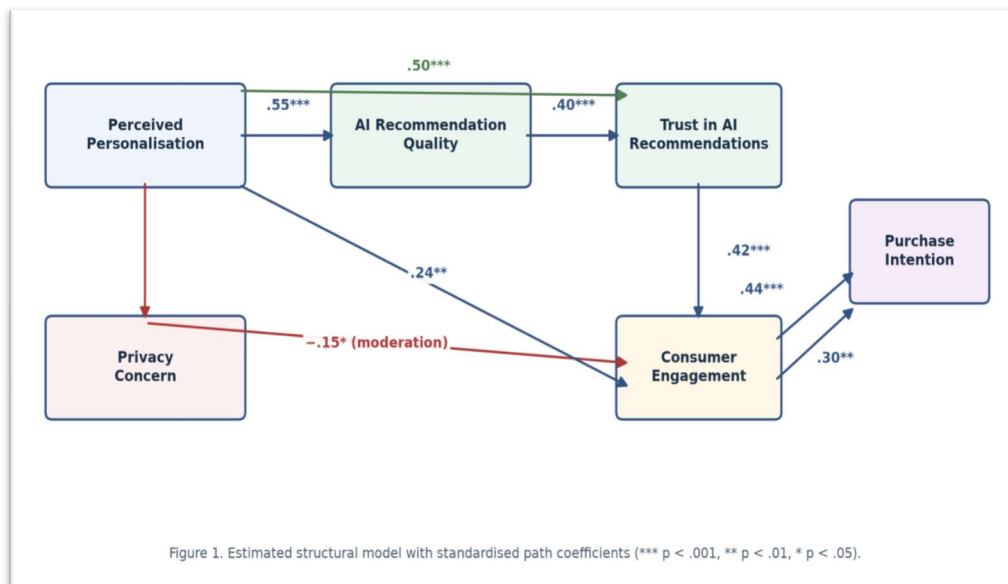


Figure 1. Estimated structural model with standardised path coefficients.

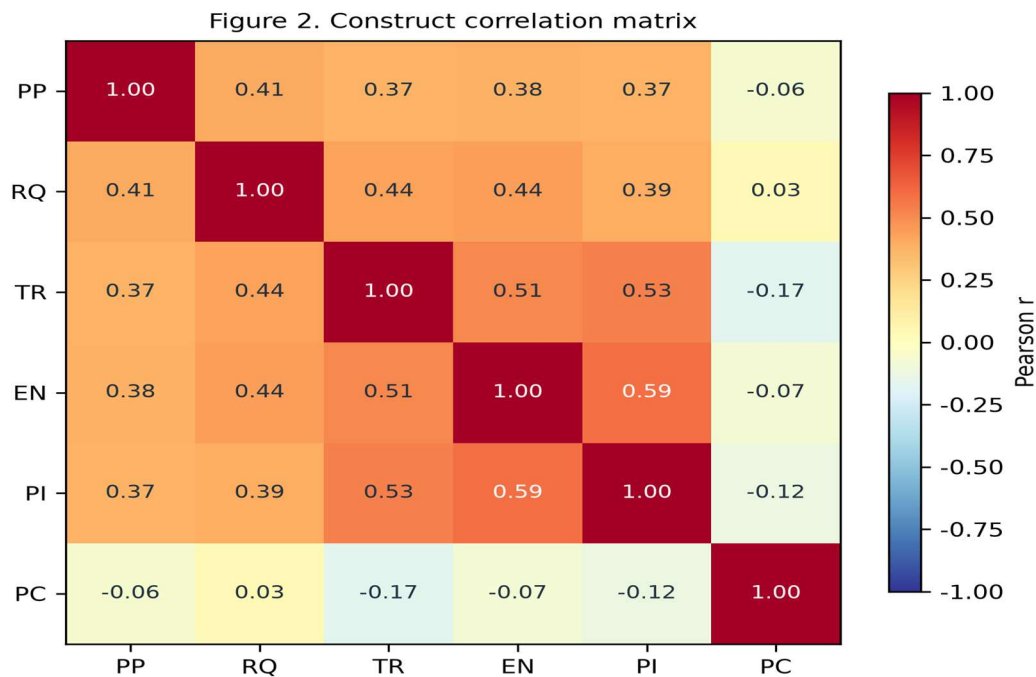


Figure 2. Correlation matrix of study constructs.

5. Discussion

The results provide a coherent picture of how algorithmic recommendation creates value in social commerce. Trust and engagement, rather than recommendation quality per se, carried the effects on purchase intention. Recommendation quality significantly predicted engagement, and it influenced purchase intention only indirectly through trust, becoming non-significant in the full model. This is the central theoretical insight: algorithmic accuracy is a necessary stimulus but not a sufficient cause of purchase. It must be metabolised into a trusting and engaged organismic state before it converts into commercial response, precisely as S-O-R theory predicts and as prior social commerce research has implied but rarely decomposed [Hajli et al., 2017; Liang, 2026].

Consumer engagement emerged as the single strongest predictor of purchase intention ($\beta = .383$), confirming that in socially embedded environments the behavioural and affective investment of the consumer, not the sophistication of the algorithm, is the proximate driver of buying. Trust exerted a significant direct effect and an additional indirect effect through engagement, indicating that trust operates both as a proximal antecedent of purchase and as a platform for deeper engagement. This dual role extends work identifying trust as the pivotal social commerce mechanism [Lăzăroiu et al., 2020] and supports serial, rather than parallel, mediation in AI-mediated retailing [Chen & Thianthai, 2026].

The privacy findings are more nuanced than the literature implies. Privacy concern correlated negatively with trust and purchase intention, and the interaction between personalisation and privacy concern was directionally negative, with the personalisation–trust slope falling by roughly a third at high privacy concern. Yet the moderation reached only marginal significance and added negligible incremental variance. Two interpretations follow. Privacy concern may function mainly as a direct drag on trust rather than as a multiplier that neutralises personalisation, which would qualify the strong version of the personalisation–privacy paradox [McKee et al., 2024]. Alternatively, in social commerce the visibility of peer endorsement may partially crowd out privacy-based reactance, because recommendations arrive socially warranted rather than purely commercially framed [Wang & Huang, 2023].

Finally, the null effect of AI-awareness on purchase intention is notable. Knowing that recommendations are machine-generated did not reduce purchase intention, which contrasts with documented algorithm aversion in high-stakes utilitarian domains [Longoni et al., 2019; Longoni & Cian, 2022] and aligns with the argument that consumers in low-stakes hedonic shopping contexts evaluate recommendation relevance rather than its provenance. Disclosure obligations may therefore be less commercially disruptive than platform managers fear, provided recommendation quality remains high.

6. Theoretical and Practical Implications

Theoretically, the study extends S-O-R into algorithmic social commerce by specifying trust and engagement as distinct, sequentially linked organismic states rather than interchangeable mediators, and by refining the personalisation–privacy paradox into a robust direct effect of privacy concern and a weak moderating one. Practically, three implications follow. First, platforms should treat recommendation accuracy as a hygiene factor and invest instead in trust-building mechanisms such as explainable recommendation rationales, transparent data practices and visible review provenance, because quality alone does not convert into purchase [Shin, 2020; Schelenz et al., 2024]. Second, engagement deserves status as a leading indicator of purchase: features that deepen cognitive and affective investment – interactive livestreams, community question-and-answer, co-creation and creator-led demonstration – are likely to outperform incremental gains in algorithmic precision [Hu & Chaudhry, 2020; Wang et al., 2022]. Third, privacy governance should target the direct erosion of trust through clear consent, data minimisation and user control, rather than attempting to dilute personalisation, which the results suggest is not the primary source of distrust.

7. Limitations and Future Research

Four limitations bound these findings. First, and most importantly, the analysis relies on a simulated, structurally calibrated dataset rather than primary field data; the observed effect sizes are therefore illustrative of the estimation procedure and of the plausible structure of the phenomenon, not empirical evidence about a real population, and the study must be replicated with genuine survey or behavioural data before its magnitudes are relied upon. Second, the cross-sectional design cannot establish temporal precedence among trust, engagement and purchase intention. Third, purchase intention is a proxy for behaviour and may overstate actual buying; linkage to transactional or clickstream data would strengthen inference. Fourth, the model omits moderators such as product category, price tier, cultural orientation and platform architecture. Future research should test the model across utilitarian and hedonic categories, treat generative-AI conversational recommenders as a distinct stimulus class, and examine whether explainability design can decouple recommendation

quality from privacy concern [Riandhi & Arviansyah, 2025; Chen & Thianthai, 2026].

8. Conclusion

AI-enabled recommendation is reshaping social commerce, but its commercial value is realised indirectly. Recommendation quality and personalisation build engagement and purchase intention primarily through trust and engagement; engagement is the strongest proximate driver of purchase; and privacy concern acts as a direct drag on trust rather than a decisive moderator of personalisation. Platforms that invest in trust and engagement, rather than in algorithmic precision alone, are best positioned to convert socially embedded attention into sustained purchase behaviour.

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