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RESEARCH

Sustainable E-Commerce in MENA: An SOR Analysis of Gen Z Purchase Intentions through Open-Source LLM (DeepSeek) Interactions, Trust, Familiarity, and Privacy Concerns

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ABSTRACT

PURPOSE: This study models how open-source large language model (LLM) recommender interaction quality (personalisation and responsiveness) affects Gen Z online purchase decisions through trust, AI familiarity, and privacy concerns using the Stimulus-Organism-Response (SOR) framework.

DESIGN/METHODOLOGY/APPROACH: We have conducted a Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis of 570 Gen Z online shoppers from Egypt, Saudi Arabia, Jordan, and Qatar.

FINDINGS: Interaction quality improved trust (β=0.2585) and AI familiarity (β=0.2943) while increasing privacy concerns (β=0.5499). Purchase intention was positively influenced by trust (β=0.2848) and privacy concerns (β=0.3583). AI familiarity showed no direct impact (β=0.0477). Model explained 47% variance in purchase intention.

ORIGINALITY/VALUE: Few studies examined trust-privacy dynamics for open-source LLM recommenders across four economies.

RESEARCH IMPLICATIONS: SOR theory application reveals trust mediates positively while high interaction quality increases privacy concerns among Gen Z.

PRACTICAL IMPLICATIONS: Retailers should optimise interaction quality while implementing transparency and user control mechanisms to address heightened privacy concerns.

KEYWORDS: *Open-Source LLMs; E-Commerce Interaction Quality; Trust-Privacy; SOR Model; Gen Z; Middle East Shopping.*

INTRODUCTION

Artificial intelligence (AI) recommender systems are now core to digital commerce (Bojic, 2024), significantly shifting consumer experiences (Ivenz and Polakova, 2024). AI recommenders offer benefits beyond conversions, potentially aiding sustainability goals (Alharethi *et al.*, 2024; Hwang *et al.*, 2014) and economic diversification by connecting niche producers with audiences.

Personalisation carries real and visible risks. Filter bubbles, data bias and surveillance backlash create a privacy-personalisation paradox in which benefits conflict with intrusion, while transparency can build trust yet heighten concern, complicating the use of LLMs in MENA e-commerce markets with high internet penetration (Martins *et al.*, 2021; Sboui *et al.*, 2024; Wang *et al.*, 2023; Bansal and Nah, 2022; Alkadi and Abed, 2023; Kemp, 2024, 2025a, 2025b).

Research on AI recommenders largely overlooks Gen Z in the MENA region despite their dominance in regional e-commerce (Alkadi and Abed, 2023; Ivenz and Polakova, 2024; Sboui *et al.*, 2024). This study addresses this gap by testing how AI personalisation shapes the trust–privacy balance and purchase intention among Gen Z across Egypt, Saudi Arabia, Jordan, and Qatar, and by reconciling perspectives outlined in Table 1. The impact is large and consequential.

Table 1: Dual Perspectives

Thematic Tension	Positive Perspective (Stimulus → Desirable Organism → Response)	Negative/Conflicting Perspective (Stimulus → Undesirable Organism → Response)
Transparency & Trust (AI explanations, data use clarity)	Builds Trust: Transparent AI recommendations enhance users' understanding and confidence. E.g., exposing how a music recommender works increases user trust (Yu and Li, 2022). Explanations of algorithm logic can improve acceptance and trust beliefs (Chen *et al.*, 2022).	Erodes Trust: Excess detail can quickly erode user trust. Highly specific explanations may overwhelm users and raise anxiety about system inference, lowering perceived reliability, and exposing flaws or mistakes can undermine confidence, as Yu and Li (2022) and Zerilli *et al.* (2022) documented.
Transparency & Trust (AI explanations, data use clarity)	Builds Trust: Transparent AI recommendations enhance users' understanding and confidence. E.g., exposing how a music recommender works increases user trust (Yu and Li, 2022). Explanations of algorithm logic can improve acceptance and trust beliefs (Chen *et al.*, 2022).	Erodes Trust: Excess detail can quickly erode user trust. Highly specific explanations may overwhelm users and raise anxiety about system inference, lowering perceived reliability, and exposing flaws or mistakes can undermine confidence, as Yu and Li (2022) and Zerilli *et al.* (2022) documented.
Personalisation & Privacy (Data-driven tailoring of content)	Drives Convenience and Purchase: Highly personalised recommendations yield convenient, relevant shopping experiences, boosting satisfaction and intent to buy. Gen Z often values the benefits of personalisation and will share data with trusted brands to get it.	Triggers Privacy Concern: Intensive personalisation often triggers privacy concern and resistance. When AI targeting undermines perceived autonomy and implies behavioural steering, consumers report greater sensitivity to data risks and reduced acceptance of tailored messages even when relevance is high. Many users push back against such tactics. This pattern reflects a privacy-personalisation paradox in which Gen Z voice strong privacy concerns while continuing to use and benefit from personalised retail apps (Cloarec *et al.*, 2024).
AI Familiarity & Adoption (Experience with and knowledge of AI)	Breeds confidence: A digital upbringing breeds real confidence. Growing up with constant exposure to AI and related tools, Gen Z reports higher comfort and self-efficacy in adopting AI-enabled services for information search, shopping, and everyday coordination across devices and channels.	Breeds Skepticism: Tech-savvy users are also more aware of AI's limitations and risks. Gen Z's digital literacy means they often take protective measures (e.g., ad- blockers, privacy settings) (Cloarec *et al.*, 2024), indicating a critical stance. Thus, greater knowledge of AI might make them harder to impress or more vigilant about potential problems (e.g., bias, errors), tempering blind trust in AI.

Source: Analysed by the authors

Table 1 summarises conflicting perspectives informing the hypotheses. This study applies the Stimulus-Organism-Response (S-O-R) framework (Mehrabian and Russell, 1974; Jacoby, 2002; Gao and Bai, 2014) to model these dynamics. The SOR model elements are Stimulus (S) = LLM Interaction Quality (personalisation, responsiveness); Organism (O) = Trust, AI Familiarity, and Privacy Concerns; Response (R) = Online Purchase Intention (Gao and Bai, 2014; Komiak and Benbasat, 2006; Malhotra *et al.*, 2004).

LITERATURE REVIEW

The Stimulus (S): DeepSeek Interaction Quality

Interaction quality, comprising personalisation and responsiveness, is crucial for AI recommenders. Personalisation enhances decision quality and engagement (Xiao and Benbasat, 2018), while responsiveness signals competence and boosts satisfaction (Yun and Park, 2022), key expectations for Gen Z in MENA.

Personalisation tailors' content to individual needs and, in contemporary systems, large language models continuously refine profiles and recommendations by learning from interaction traces and contextual cues (Xiao and Benbasat, 2018; Zanker *et al.*, 2019). Responsiveness means speed and relevance. It predicts loyalty (Chen *et al.*, 2022). Yet, high interaction quality does not ensure trust or adoption. Over-personalisation often feels invasive to users (Malhotra *et al.*, 2004; Sun *et al.*, 2023). Moreover, fast responses can hide weak relevance and misfit recommendations, a problem especially acute for security-conscious Gen Z users who scrutinise data practices (Ivenz and Polakova, 2024; Sboui *et al.*, 2024).

The Organism (O): Internal States

This study models three key internal states influenced by interaction quality: trust, AI familiarity, and privacy concerns.

Trust in DeepSeek

Trust in system reliability drives Gen Z purchase intention, and alongside ability, integrity and benevolence, AI-specific qualities such as fairness and explainability also shape trust, while evidence on the role of transparency remains mixed (McKnight *et al.*, 2002; Komiak and Benbasat, 2006; Shin and Park, 2019; Yu and Li, 2022; Zerilli *et al.*, 2022). Responsive, personalised interaction signals competence and benevolence, building trust and countering initial scepticism among Gen Z users (Mayer *et al.*, 1995; McKnight *et al.*, 2002; Xiao and Benbasat, 2018). Trust drives purchase intention for Gen Z.

H1: DeepSeek's interaction quality (high personalisation and responsiveness) positively influences users' trust in the recommender.

AI Familiarity

AI familiarity reflects comfort and knowledge with AI systems (Gefen, 2000; Komiak and Benbasat, 2006). While traditionally seen as preceding trust (Gefen, 2000), positive interaction quality (IQ) with LLMs might enable familiarity by encouraging exploration and learning, boosting usefulness perceptions (Arce-Urriza *et al.*, 2025; Komiak and Benbasat, 2006; Li *et al.*, 2024).

H2: DeepSeek's interaction quality (high personalisation and responsiveness) positively influences users' AI familiarity.

Privacy Concerns

Privacy concerns involve perceived risks of data misuse/lack of control from data harvesting by AI recommenders (Malhotra *et al.*, 2004; Rosenberger *et al.*, 2025). High IQ, particularly personalisation, can heighten these concerns by making data collection salient (Cloarec *et al.*, 2024; Kim *et al.*, 2023). This aligns with communication privacy management theory and the "uncanny accuracy" effect increasing vigilance (Barth *et al.*, 2022; Petronio and Child, 2020). Thus, we hypothesise IQ positively influences privacy concerns.

H3: DeepSeek's interaction quality (high personalisation and responsiveness) positively influences users' privacy concerns.

Response (R): Online Purchase Intention

Online purchase intention (PI), the likelihood of acting on recommendations, is the Response (R) (Gao and Bai, 2014; Spears and Singh, 2004). It stems from appraising benefits and risks, influenced by trust (+) and privacy concerns (- typically) (Bansal and Nah, 2022; Sulistyowati and Husda, 2023). While recommenders often boost purchases (Feng *et al.*, 2024), contextual factors matter (Sboui *et al.*, 2024). Purchase intention is influenced by the preceding organismic states.

The Influence of Trust consistently drives PI by reducing perceived risk (Ganesan and Hess, 1997; Sulistyowati and Husda, 2023). This may be amplified in low institutional trust contexts like the sampled markets (Sheth, 2020).

H4: Gen Z trust in DeepSeek's positively influences their online purchase intention.

Privacy concerns shape purchase intention in complex ways. Perceived data risks generally lower purchase intention, a pattern especially salient in MENA markets, yet the effect can be moderated or even reversed by user control and by collectivist norms or a sense of agency (Bansal and Nah, 2022; Saxena and Thakur, 2024; Haddad, 2024; Alkadi and Abed, 2023; Brough and Martin, 2020; Kim *et al.*, 2023).

H5: There is a significant relationship between Gen Z privacy concern and online purchase intention.

Familiarity alone may not shape purchase intention. Contrary to the TAM (Venkatesh and Davis, 2000), Gen Z's exposure saturates effects, and familiarity lacks the trust needed for purchase, so this study expects no effect on purchase intention (Cang *et al.*, 2022; Hoff and Bashir, 2015).

H6: AI familiarity is not significantly associated with online purchase intention.

Drawing on prior research, this study proposes a Stimulus-Organism-Response (SOR) model that integrates interaction quality, trust, AI familiarity, and privacy concerns to explain their joint effects on Gen Z consumers' purchase intentions. Figure 1 visualises the proposed relationships.

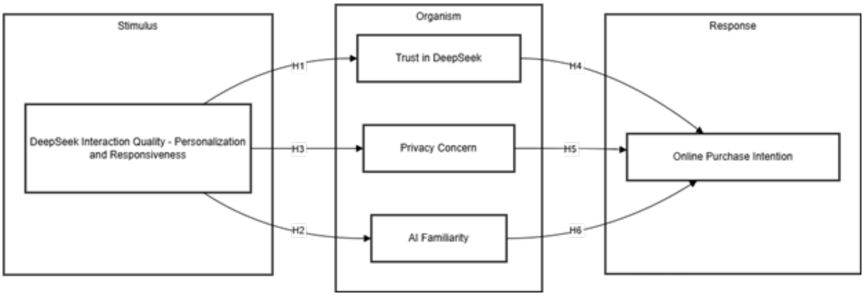

Figure 1: Research Model

Source: Developed by the authors

RESEARCH METHODOLOGY

This study used a quantitative, cross-sectional survey. Gen Z online shoppers in Egypt, Jordan, Qatar, and Saudi Arabia were surveyed, and the study estimated the model using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4 following the guidance of Hair and Alamer (2022) and Hair *et al.* (2019).

Sampling and data collection were used a single wave. A 2024 Qualtrics survey captured SOR perceptions of "DeepSeek" and produced 570 Gen Z respondents aged 18–26 from Egypt, Jordan, Qatar, and Saudi Arabia, meeting PLS-SEM sample size recommendations (Guenther *et al.*, 2023; Hair and Alamer, 2022). All respondents had prior online purchase and AI chatbot experience. Items with loading below 0.70 were removed, specifically tr1, f1, f5, and PI4 (see Table 4).

RESULTS

Sample Demographics

The final sample comprised 570 Gen Z online shoppers aged 18–26 from Egypt, Jordan, Qatar, and Saudi Arabia, with Table 2 reporting gender, occupation, country distribution, and AI usage frequency and familiarity. Key attributes are fully and clearly reported.

Table 2: Sample Demographics (N = 570)

Characteristic	*Category*	*n*	*%*
Gender	Female	378	66.3
	Male	192	33.7
Country	Qatar	45	7.9
	Egypt	320	56.1
	Jordan	150	26.3
	Saudi Arabia	55	9.7
Occupation	Student	332	58.2
	Employed	144	25.3
	Working Student	60	10.5
	Unemployed	34	6
Use Frequency	Always	116	20.4
	Frequently	200	35.1
	Occasionally	152	26.7
	Rarely	102	17.9
AI Apps Used	DeepSeek	456	80.0
	ChatGPT	314	55.1
	Others	106	18.6

Source: Analysed by the authors

Note: "AI Apps Used" allowed multiple responses per respondent.

Measurement Model Assessment

The measurement model demonstrated acceptable reliability and validity. Detailed reliability and validity results are presented in Table 3, 6, and 7.

Table 3: Measurement Model: Reliability and Convergent Validity

Construct	*Cronbach's α*	*ρ_A*	*CR*	*AVE*
DeepSeeks Interaction Quality	0.923	0.928	0.936	0.648
Trust	0.746	0.761	0.855	0.663
AI Familiarity	0.672	0.675	0.819	0.602
Privacy Concern	0.830	0.831	0.887	0.664
Purchase Decision	0.760	0.766	0.862	0.676

Source: Analysed by the authors

Note: All α and CR > 0.70; AVE > 0.50 for all constructs, establishing convergent validity.

Table 4: Indicator Retention

Construct	*Retained Indicators*	*Dropped Indicators (poor loading)*
DeepSeeks Interaction Quality (iq)	iq1, iq2, iq3, iq4, iq5, iq6, iq7, iq8	–
Trust (tr)	tr2, tr3, tr4	tr1
AI Familiarity (f)	f2, f3, f4	f1, f5
Privacy Concern (pc)	pc1, pc2, pc3, pc4	–
Purchase Decision (PI)	PI1, PI2, PI3	PI4

Source: Analysed by the authors

Note: tr1, f1, f5, and PI4 were removed due to outer loadings < 0.70 (see Table 3).

Outer Loadings

All retained items loaded strongly (≥ 0.75) on their constructs (Table 5).

Table 5: Outer Loadings

Item	*Loading*
DeepSeeks Interaction Quality	
iq1	0.768
iq2	0.800
iq3	0.786
iq4	0.836
iq5	0.808
iq6	0.844
iq7	0.765
iq8	0.830
Trust	
tr2	0.772
tr3	0.864
tr4	0.804
AI Familiarity	
f2	0.754
f3	0.820
f4	0.751
Privacy Concern	
pc1	0.802
pc2	0.844
pc3	0.844
pc4	0.765

Item	*Loading*
Purchase Decision	
PI1	0.820
PI2	0.863
PI3	0.782

Source: Analysed by the authors

Discriminant Validity

Discriminant validity was confirmed by both the Fornell–Larcker criterion (AVE on diagonals > inter-construct correlations) and the HTMT ratio (< 0.85). See Table 6 (Fornell–Larcker) and Table 7 (HTMT).

Table 6: Fornell–Larcker Criterion

	1. DeepSeeks IQ	*2. Trust*	*3. AI Fam.*	*4. Privacy*	*5. Purchase*
1. DeepSeeks IQ (√AVE=0.805)	0.805	0.258	0.294	0.550	0.338
2. Trust (√AVE=0.814)	0.258	0.814	0.347	0.465	0.397
3. AI Familiarity (√AVE=0.775)	0.294	0.347	0.775	0.540	–0.022
4. Privacy Concern (√AVE=0.815)	0.550	0.465	0.540	0.815	0.210
5. Purchase Decision (√AVE=0.822)	0.338	0.397	–0.022	0.210	0.822

Source: Analysed by the authors

Note: Diagonals (bold) exceed corresponding off-diagonals, satisfying the Fornell–Larcker test.

Table 7: Heterotrait–Monotrait Ratio (HTMT)

	1. DeepSeeks IQ	*2. Trust*	*3. AI Fam.*	*4. Privacy*	*5. Purchase*
1. DeepSeeks IQ	1.000	0.291	0.366	0.618	0.580
2. Trust	0.291	1.000	0.455	0.589	0.618
3. AI Familiarity	0.366	0.455	1.000	0.540	0.400
4. Privacy Concern	0.618	0.589	0.540	1.000	0.642
5. Purchase Decision	0.580	0.618	0.400	0.642	1.000

Source: Analysed by the authors

Note: All HTMT < 0.85, further confirming discriminant validity.

Structural Model Assessment

After confirming the adequacy of the measurement model, the structural model and hypothesised relationships were evaluated, as illustrated in Figure 2.

Collinearity and Model Fit

No significant collinearity issues were detected among predictor constructs, as all Variance Inflation Factor (VIF) values were below the threshold of 3. The overall model fit indices were acceptable: SRMR = 0.041, dULS = 0.970, and dG = 0.278, which fall within recommended range (Hair *et al.*, 2019).

Hypothesis Testing

Hypotheses were tested using bootstrapping (5,000 resamples). Results are shown in Table 8.

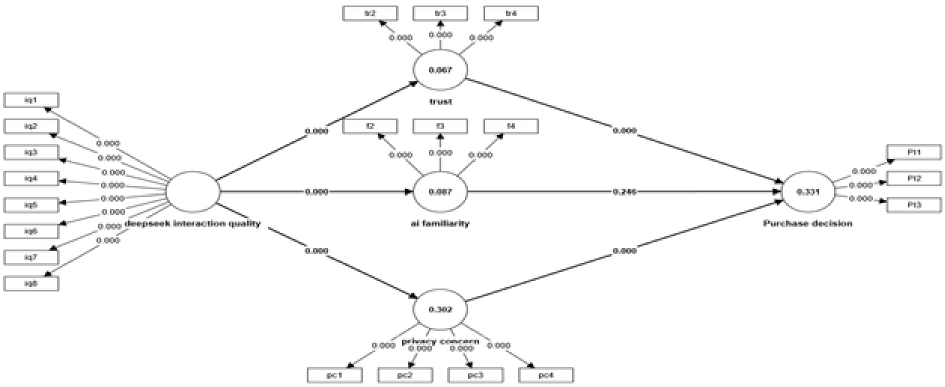

Figure 2: Structural Model with Standardized Path Coefficients

Source: Constructed by the authors

Table 8: Hypotheses Testing and Effect Sizes

Path	*β*	*t-value*	*p-value*	*f²*	*Hypothesis*
H1: DeepSeeks IQ → Trust	0.2585	4.72	< 0.001	0.040	Supported
H2: DeepSeeks IQ → Privacy Concern	0.5499	9.12	< 0.001	0.008	Supported
H3: DeepSeeks IQ → AI Familiarity	0.2943	5.35	< 0.001	0.082	Supported
H4: Trust → Purchase Decision	0.2848	4.93	< 0.001	0.027	Supported
H5: Privacy Concern → Purchase Decision	0.3583	6.24	< 0.001	0.028	Supported
H6: AI Familiarity → Purchase Decision	0.0477	0.54	0.587	0.005	Not supp.

Source: Analysed by authors

Explained Variance (R^2) and Effect Sizes (f^2): The model explained substantial variance in endogenous constructs: Trust (R^2=0.067), AI Familiarity (R^2=0.087), Privacy Concern (R^2=0.302), and Purchase Intention (R^2=0.47). Regarding effect sizes (f^2), Interaction Quality had small-to-medium effects on AI Familiarity (f^2=0.082) and Trust (f^2=0.040), but an exceedingly small effect on Privacy Concern (f^2=0.008). For Purchase Intention, Privacy Concern (f^2=0.028) and Trust

(f^2=0.027) showed small effects, while the direct effect of Interaction Quality (f^2=0.000) and the effect of AI Familiarity (f^2=0.005) were negligible.

Predictive Relevance (Stone-Geisser Q^2): Blindfolding analysis (D=7) confirmed the model's predictive relevance, with all Stone-Geisser Q^2 values exceeding zero. Results indicated moderate predictive relevance for Purchase Intention (Q^2=0.260), small-to-moderate for Privacy Concern (Q^2=0.195), and small for AI Familiarity (Q^2=0.046) and Trust (Q^2=0.041), as detailed in Table 9.

Table 9: Stone–Geisser Q²

Endogenous Construct	*SSO*	*SSE*	*Q²*	*Interpretation*	*Hypothesis*
Purchase Decision	1,710.00	1,265.64	0.260	Moderate predictive relevance	Supported
AI Familiarity	1,710.00	1,630.73	0.046	Small predictive relevance	Supported
Privacy Concern	2,280.00	1,835.63	0.195	Small-to-moderate predictive relevance	Supported
Trust	1,710.00	1,639.80	0.041	Small predictive relevance	Supported

Source: Analysed by authors

SSO = *sum of squares of observations; SSE = sum of squared prediction errors;* $Q^2 = 1 - (SSE/SSO)$.

PLSpredict: Out-of-sample predictive power was assessed using PLSpredict (10-fold cross-validation). The model's prediction errors (RMSE) were lower than a naïve linear benchmark for all key endogenous constructs. Furthermore, Q^2_predict values > 0 for all indicators confirmed medium predictive power following established guidelines (Shmueli *et al.*, 2019).

DISCUSSION

This study reveals how open-source LLM interaction quality triggers complex psychological responses among Gen Z in MENA markets, challenging established Western models.

Interaction quality has a clear dual impact. It significantly increased trust ($\beta = 0.26$, $p < 0.001$) and AI familiarity ($\beta = 0.29$, $p < 0.001$), supporting H1 and H2. The pattern accords with trust models and with signalling accounts in which responsiveness signals competence and personalisation signals benevolence (Komiak and Benbasat, 2006; Mayer *et al.*, 1995). Open-source cues can build trust much like brand reputation, extending findings from Western contexts (Shin and Park, 2019; Xiao and Benbasat, 2018; Yun and Park, 2022). Together, the results point to a trust- then -familiarity sequence in interactive AI, contrasting with traditional adoption paths that emphasise familiarity first, consistent with conversational, co-adaptive use contexts (Gefen, 2000; Springer and Whittaker, 2020).

However, supporting H3, the same interaction quality dramatically increased privacy concerns (β=0.55, p<0.001), showing the strongest path in our model (Seaborn *et al.*, 2023). This contradicts privacy calculus theory where benefits typically offset concerns. Instead, sophisticated AI interactions make data collection salient, triggering what could be called "competence-induced vigilance"; users recognise the AI's capabilities and become more protective. These findings align with communication privacy management theory, which predicts boundary turbulence when granular insights strain disclosure rules, and show Gen Z vigilance towards large language models that infer sensitive information (Petronio and Child, 2020). Gen Z monitor LLMs very closely.

Trust and privacy concerns both increased purchase intention. Trust had a positive effect ($\beta = 0.28$, $p < 0.001$), supporting H4, and was stronger in low institutional trust settings, including MENA markets (Ganesan and Hess, 1997; Sheth, 2020). Privacy concerns also increased intention, supporting H5 and being consistent with users treating risk as a transaction cost; collectivist norms reframing sharing; and concern signalling involvement rather than avoidance of purchase (T. Kim *et al.*, 2023; Alkadi and Abed, 2025; Bansal and Nah, 2022).

AI familiarity did not affect purchase intention, supporting H6. Contrary to TAM expectations, the null effect ($\beta = 0.05$, ns) likely reflects baseline exposure among Gen Z and missing trust cues that turn familiarity into buying bevaiour (Cang *et al.*, 2022; Hoff and Bashir, 2015).

THEORETICAL CONTRIBUTIONS

These results revise core SOR assumptions for conversational AI. High interaction quality produced organismic states that elevated both trust and privacy concerns, yet each path increased purchase intention, indicating that in communal sharing contexts, privacy concerns can operate as an engagement signal. The sequence also appeared inverted, with trust enabling familiarity rather than the reverse, which suggests updating SOR- and TAM-based frameworks for co-adaptive, conversational interactions.

MANAGERIAL IMPLICATIONS

Managers should rethink AI deployment choices. Rather than dampening privacy salience, position data requests as participatory acts that grant users meaningful control, and prioritise visible competence through locally accurate results and cultural relevance to build trust where it matters for purchase. Do not invest in broad AI education campaigns if familiarity does not move buying intention. For open-source models, use code auditability as a trust cue and pair it with granular controls that channel heightened privacy awareness into productive engagement. Do not rely on conversion alone; track trust sentiment and perceived control as leading indicators, because concerned users are often the most engaged buyers.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Several limitations qualify these findings clearly. External validity is constrained by our focus on a single model, by self-reported intentions that may overstate behaviour and enable reverse causality, by a cross-sectional design, and by a Gen Z MENA sample. Results may not extend to closed-source systems, different governance models, or older cohorts. Generalisation beyond these bounds must be approached cautiously.

Future work should test behaviour directly. Track actual purchases across multiple LLMs, including closed-source alternatives, using longitudinal designs that identify temporal sequencing, measure cultural values explicitly, and experimentally manipulate interaction quality in varied markets. Include older cohorts to permit generational contrasts and integrate social commerce signals to capture richer pathways from interaction to purchase. Clarify whether privacy concerns reflect engagement or measurement error.

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