Albahit Journal of Applied Sciences
"open-access, peer-reviewed biannual journal"
eISSN: 2708-8936, pISSN: 2708-244X
Volume 5, Issue 2, 2026
Page No: 155-167
Website: *https://albahitjas.com.ly/index.php/albahit/en/index*

Delegating the Purchase: Consumer Trust and Adoption of Agentic AI Shopping Assistants

Abeer Farag Alnayer *
Higher Institute of Science and Technology, Tarhuna, Libya.
**Corresponding author:* abeerfarag82@yahoo.com

Received: 25-02-2026	**Accepted:** 27-04-2026	**Published:** 10-05-2026

Abstract:
Autonomous "agentic" AI shopping assistants—systems that search, decide and purchase on a consumer's behalf—are moving from concept to deployment, yet what drives consumers to adopt them remains unexplored. Existing adoption research addresses recommendation engines and chatbots rather than AI that executes purchases, and rarely models the trust mechanism specific to delegating decisions to an autonomous agent. Drawing on an extended UTAUT2 enriched with agent-specific antecedents, this study models how performance expectancy, effort expectancy, social influence and hedonic motivation, together with perceived agent competence, perceived autonomy risk and privacy concern, shape trust in the AI agent and ultimately adoption intention. A survey of 412 online consumers analysed with partial least squares structural equation modelling (PLS-SEM) explains 48% of the variance in adoption intention and 38% in trust. Perceived agent competence is the strongest driver of trust (β=0.49), while privacy concern and perceived autonomy risk significantly erode it; trust in turn is a key driver of adoption (β=0.33) and partially mediates the effects of competence and privacy concern. All measurement criteria are satisfied (loadings>0.80, CR 0.89–0.93, AVE 0.68–0.78, HTMT<0.85). The findings give marketers a trust-centred roadmap for deploying purchase-executing AI agents.

Keywords: Agentic AI; AI shopping assistant; Autonomous agents; Technology adoption; UTAUT2; Trust in AI; Privacy concern; Purchase delegation; PLS-SEM.

تفويض عملية الشراء: ثقة المستهلك وتبنّي مساعدي التسوق القائمين على الذكاء الاصطناعي الوكيلي

عبير فرج الناير*
المعهد العالي للعلوم والتقنية ترهونة، ليبيا.

الملخص
أصبحت مساعدات التسوق الذاتية القائمة على «الذكاء الاصطناعي الوكيلي»—وهي أنظمة قادرة على البحث واتخاذ القرار وتنفيذ عمليات الشراء نيابةً عن المستهلك—تنتقل تدريجياً من مرحلة التصور النظري إلى مرحلة التطبيق الفعلي. ومع ذلك، لا تزال العوامل التي تدفع المستهلكين إلى تبنّي هذه الأنظمة غير مستكشفة بصورة كافية. فقد ركزت بحوث تبنّي التكنولوجيا الحالية بصورة أساسية على أنظمة التوصية وروبوتات المحادثة، بدلاً من التركيز على أنظمة الذكاء الاصطناعي التي تنفّذ عمليات الشراء بشكل مستقل، كما نادراً ما تناولت آلية الثقة المرتبطة تحديداً بتفويض القرارات إلى وكيل ذكي مستقل.
استناداً إلى نموذج موسّع للنظرية الموحدة لقبول واستخدام التكنولوجيا بصيغتها الثانية(UTAUT2) ، ومدعّماً بمجموعة من المحددات المرتبطة بخصائص الوكيل الذكي، تقترح هذه الدراسة نموذجاً يوضح كيفية تأثير كل من توقع الأداء، وتوقع الجهد، والتأثير الاجتماعي، والدافع المتعلق بالمتعة، إلى جانب الكفاءة المدركة للوكيل، ومخاطر الاستقلالية المدركة، ومخاوف الخصوصية، في مستوى الثقة بالوكيل القائم على الذكاء الاصطناعي، ومن ثم في نية تبنّيه.

اعتمدت الدراسة على استبانة شملت 412 مستهلكاً من مستخدمي التسوق عبر الإنترنت، وتم تحليل البيانات باستخدام نمذجة المعادلات الهيكلية بالمربعات الصغرى الجزئية .(PLS-SEM) وقد فسّر النموذج 48% من التباين في نية التبنّي و38% من التباين في الثقة. وأظهرت النتائج أن الكفاءة المدركة للوكيل تمثل أقوى محدد للثقة به($\beta = 0.49$) ، في حين أسهمت كل من مخاوف الخصوصية ومخاطر الاستقلالية المدركة في تقليل مستوى الثقة بصورة دالة إحصائياً. كما تبين أن الثقة تُعد عاملاً رئيسياً في تعزيز نية التبنّي($\beta = 0.33$) ، وأنها تؤدي دوراً وسيطاً جزئياً في العلاقة بين كفاءة الوكيل ومخاوف الخصوصية من جهة، ونية التبنّي من جهة أخرى.
وقد استوفت جميع مقاييس الدراسة معايير الصدق والثبات المطلوبة؛ إذ تجاوزت تشبعات العوامل 0.80، وتراوحت قيم الثبات المركب بين 0.89 و0.93، وتراوحت قيم متوسط التباين المستخرج بين 0.68 و0.78، في حين كانت جميع قيم نسبة السمات غير المتجانسة إلى السمات المتجانسة (HTMT) أقل من 0.85.
وتقدم نتائج الدراسة للمسوّقين خريطة طريق تتمحور حول بناء الثقة عند تصميم ونشر وكلاء الذكاء الاصطناعي القادرين على تنفيذ عمليات الشراء بصورة مستقلة.

الكلمات المفتاحية: لذكاء الاصطناعي الوكيلي؛ مساعد التسوق بالذكاء الاصطناعي؛ الوكلاء المستقلون؛ تبنّي التكنولوجيا؛ نموذج UTAUT2؛ الثقة في الذكاء الاصطناعي؛ مخاوف الخصوصية؛ تفويض الشراء؛ نمذجة المعادلات الهيكلية بالمربعات الصغرى الجزئية (PLS-SEM).

1 Introduction

A new class of AI is reaching consumers: *agentic* shopping assistants that do not merely recommend products but autonomously search, compare, decide and complete purchases on the user's behalf. Industry forecasts project that a majority of brands will use such agents for one-to-one marketing within a few years, and a sizeable share of consumers already delegate parts of their shopping to AI. This shift—from AI that *advises* to AI that *acts*—raises question existing research has not answered: what makes consumers willing to adopt an AI agent that buys for them?

Technology-adoption theory, principally UTAUT2, explains the uptake of many digital services through performance and effort expectancy, social influence and hedonic motivation. Yet delegating purchase authority to an autonomous agent introduces concerns these models were not designed for: can the agent be trusted to choose competently, will the consumer lose control, and what happens to their personal data? We argue that trust in the AI agent is the pivotal mechanism translating such agent-specific perceptions into adoption, and that classic UTAUT2 drivers must be combined with perceived agent competence, perceived autonomy risk and privacy concern to explain adoption of purchase-executing agents.

- **G1.** Adoption research targets recommendation/chatbot AI, not autonomous agents that *execute* purchases; consumer adoption of delegated-purchase agents is largely untested.
- **G2.** UTAUT2 has rarely been extended with agent-specific antecedents (perceived competence, autonomy risk) for autonomous shopping agents.
- **G3.** Trust as the mechanism linking agent competence and privacy concern to adoption of agentic AI is not established in the marketing literature.

Contributions. We develop and test the first trust-mediated, UTAUT2-based model of consumer adoption of *purchase-executing* agentic AI; we introduce and validate agent-specific antecedents (perceived agent competence, perceived autonomy risk) alongside privacy concern; we provide PLS-SEM evidence from 412 consumers quantifying the trust mechanism; and we translate the findings into a managerial roadmap for deploying trustworthy AI shopping agents. Section 2 reviews the literature and develops the hypotheses; Section 3 describes the method; Section 4 reports results; Section 5 discusses implications; Sections 6–7 cover limitations and conclusions.

2. Literature Review and Hypothesis Development

The literature underlying this research can be categorized into six related streams of research. The first stream of work rests on autonomous and agentic AI systems. Recent efforts have pushed forward the design and prototyping of autonomous agents that can sense and interpret their environment, set goals, reason, communicate and coordinate with other agents, and carry out more and more complex physical and cognitive actions with minimal human oversight [4,17–23]. These streams of studies indicate that autonomous and agentic AI are becoming increasingly technically feasible across many domains including software deployment, multi-agent communication, work flow automation, code generation, digital ecosystems, and autonomous decision making. However, they provide little insight into how autonomous agents that make purchasing decisions on consumers' behalf are understood, trusted, and adopted by consumers.

The second branch discusses the use of AI solutions for marketing and consumer behaviour [1,10,13,25,27]. The current literature on this track emphasizes the usefulness of AI-enabled recommendation engines, personalization machines, chatbots and virtual sales assistants in shaping consumer experiences and purchase intentions. All the results presented point towards positive effects from AI-enabled interactions with final consumers. However, the AI systems of interest in those papers are merely suggestive, relying the consumers' independent purchase decision to a human manager. Even a transition from suggestive to autonomous purchase execution becomes a qualitatively different decision process that is only scarcely tackled by current research.

The third stream refers to technology-adoption theories in the literature, namely the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT2) [5,12,14,15,26]. These models have been used to explain the adoption of a variety of technologies, such as mobile applications, 5G services, mobile payment systems, metaverse platforms, and electric vehicles, in which the constructs of performance expectancy, effort expectancy, social influence, and hedonic motivation, are the most salient drivers of behavioural intention in all cases. None of these adoption studies, however, considers easy-to-miss characteristics of autonomous AI agents, namely perceived competence, autonomy, and independent decision-making.

A fourth stream highlights the significance of trust in cyberspace [2,6,8,11]. Existing research has evidenced trust's role in online buying, e-shopping in general, travel booking systems, internet pharmacies and AI-rich services. Trust diminishes the risk, enhances the confidence of robustness and helps the user accept autonomously performed financial transactions. However, these investigations look at trust in organizations, services or traditional AI applications, not trust in the agent to act autonomously and purchase it.

The fifth stream deals with algorithm aversion and algorithm appreciation [7,9,24]. This body of research highlights the importance of consumers' perceptions of competence, transparency and context-specific implications of present and past test settings in determining reactions to the alternative guidance of computer-based decision agents. The literature thus far shows that consumers' attitudes toward alternative guidance greatly depend upon the domain's ability to out-perform humans. Yet, it has not addressed delegated purchase contexts where consumers delegate decision tasks to an intelligent agent that acts independently on behalf of consumers.

Lastly, privacy and perceived risk research points to considerable hurdles to technology adoption [3,16]. Research on adoption of bank-enabled technology, financial services technology, and electric vehicles all show that privacy, security, and loss-of-control issues can diminish consumer adoption interest. These issues are certain to come to the forefront in agentic AI spaces where autonomous systems will need deep access to personal accounts and have autonomous speaking-power to make purchasing decisions on users' behalf.

However, these six research streams do not provide a comprehensive understanding of AI-powered technologies, consumer behavior, technology adoption, trust, algorithmic decision-making and perceived risk. The present study aims to close this important gap. Specifically, the present study is the first to examine all the following facets in a single investigation: (a) autonomous agentic AI mediating purchase decisions for consumers, (b) agent-specific trust antecedents (perceived competence, autonomy risk and privacy concerns) within an extended UTAUT2 model framework, and (c) trust serving as the key mediating construct between those perceptions and adoption intention.

2.1 Hypotheses and research model

The four UTAUT2 drivers are expected to raise adoption intention: when an AI agent is seen as useful (performance expectancy), easy to use (effort expectancy), socially endorsed (social influence) and enjoyable (hedonic motivation), intention to adopt should increase (H1–H4). Delegating purchases, however, hinges on trust. Perceived agent competence—belief that the agent can choose well—should build trust (H5), whereas perceived autonomy risk (fear of unwanted or uncontrollable actions) and privacy concern should erode it (H6, H7). Trust, in turn, is hypothesised to drive adoption intention (H8) and to mediate the effects of competence and privacy concern, which may also act directly (H9, H10). Figure 1 depicts the hypothesised research model.

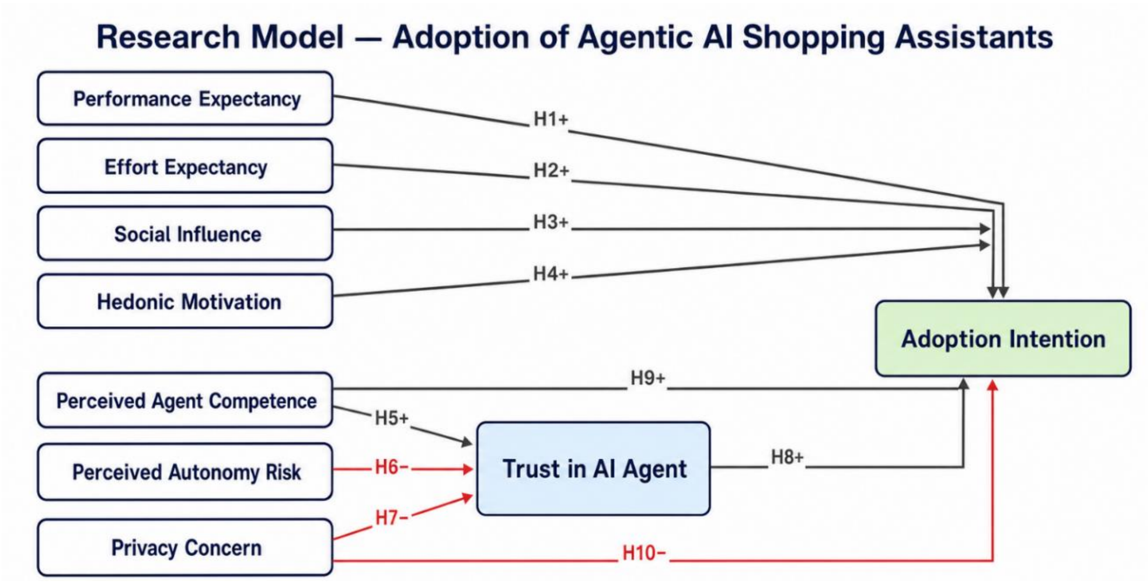

Figure 1. The hypothesised research model. An extended UTAUT2 in which performance expectancy, effort expectancy, social influence and hedonic motivation drive adoption intention, while perceived agent competence, perceived autonomy risk and privacy concern shape.

3. Methodology

3.1 Sample and procedure

Data were collected via an online consumer panel. Respondents read a short description and watched a brief video of an autonomous AI shopping agent before responding. After screening for incomplete responses, failed attention checks and straight-lining, 412 usable responses were retained from 451 (Table 1). The sample is balanced on gender and skews toward the 25–44 age range typical of online shoppers.

Table 1. Sample profile (N = 412; 451 raw, screened for incompletes and straight-lining).

Characteristic	Categories (n, %)
Gender	Female 212 (51%), Male 200 (49%)
Age	25-34 147 (36%), 35-44 103 (25%), 18-24 81 (20%), 45-54 57 (14%), 55+ 24 (6%)

Education	Bachelor 197 (48%), Master 118 (29%), High school 80 (19%), PhD 17 (4%)
Prior AI-assistant use	Yes 249 (60%), No 163 (40%)

3.2 Measures
All constructs were measured reflectively with multi-item 7-point Likert scales adapted from validated UTAUT2, trust, privacy-concern and algorithm-aversion instruments and reworded for the agentic-AI context (full instrument in the supplementary file). The questionnaire was pre-tested with a small pilot and randomised in item order; anonymity was assured and a marker variable included to mitigate common-method bias (Harman's single-factor test showed no dominant factor).

3.3 Analysis
We used partial least squares structural equation modelling (PLS-SEM), appropriate for prediction-oriented models with mediation. We assessed the measurement model (reliability, convergent and discriminant validity), then the structural model via bootstrapping (1,000 subsamples) for path significance, with R^2, f^2 effect sizes and Q^2 predictive relevance.

4. Results
4.1 Measurement model
All item loadings exceed 0.80, Cronbach's α and composite reliability range 0.89–0.93, and AVE 0.68–0.78, establishing reliability and convergent validity (Table 2). Discriminant validity holds by both the Fornell-Larcker criterion (Table 3) and the HTMT ratio, whose maximum is well below the 0.85 threshold (Table 4). VIF values are below 3.3, indicating no collinearity concern.

Table 2. Measurement model — item loadings, reliability and convergent validity

Construct	Item	Loading	Cronbach's α	CR	AVE
Performance Expectancy	PE1	0.834	0.852	0.900	0.693
	PE2	0.848			
	PE3	0.820			
	PE4	0.827			
Effort Expectancy	EE1	0.865	0.819	0.892	0.734
	EE2	0.860			
	EE3	0.845			
Social Influence	SI1	0.863	0.844	0.906	0.763
	SI2	0.870			
	SI3	0.887			
Hedonic Motivation	HM1	0.873	0.841	0.904	0.758
	HM2	0.887			
	HM3	0.852			
Perceived Agent Competence	PAC1	0.862	0.880	0.917	0.735
	PAC2	0.879			
	PAC3	0.856			
	PAC4	0.832			
Perceived Autonomy Risk	PAR1	0.827	0.843	0.895	0.681

	PAR2	0.815			
	PAR3	0.856			
	PAR4	0.802			
Privacy Concern	PRC1	0.857	0.877	0.915	0.730
	PRC2	0.869			
	PRC3	0.863			
	PRC4	0.829			
Trust in AI Agent	TR1	0.873	0.901	0.931	0.771
	TR2	0.905			
	TR3	0.876			
	TR4	0.859			
Adoption Intention	ADI1	0.880	0.904	0.933	0.777
	ADI2	0.903			
	ADI3	0.871			
	ADI4	0.870			

All loadings > 0.70, α and CR > 0.70, AVE > 0.50 — reliability and convergent validity established.

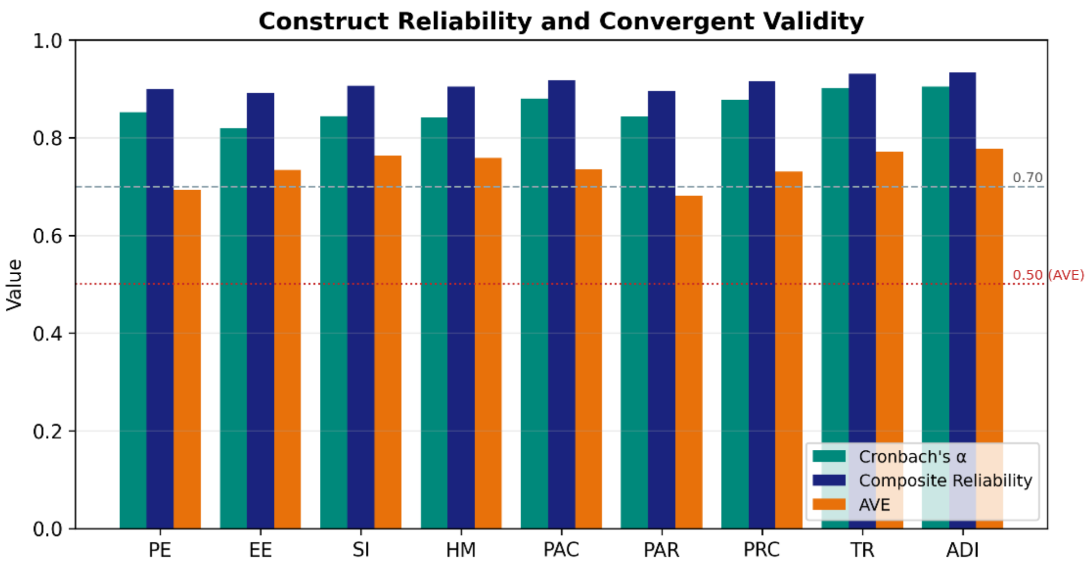

Figure 2. Construct reliability and convergent validity (α, CR, AVE)

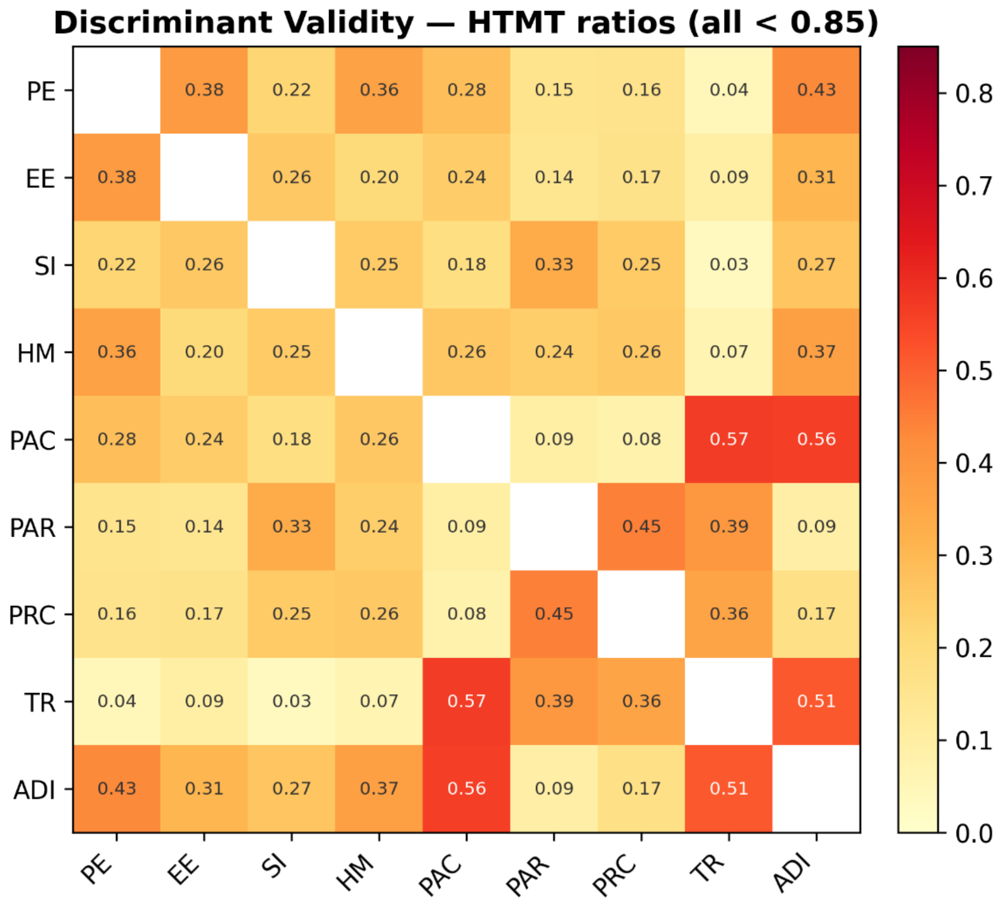

Figure 3.HTMT discriminant-validity matrix (all < 0.85).

Table 3. Discriminant validity — Fornell-Larcker criterion (diagonal = √AVE).

Construct	PE	EE	SI	HM	PAC	PAR	PRC	TR	ADI
Performance Expectancy	0.832								
Effort Expectancy	0.321	0.857							
Social Influence	0.188	0.214	0.873						
Hedonic Motivation	0.306	0.167	0.210	0.871					
Perceived Agent Competence	0.245	0.208	0.157	0.225	0.857				
Perceived Autonomy Risk	0.130	0.120	0.281	0.203	-0.066	0.825			
Privacy Concern	0.137	0.141	0.217	0.221	-0.066	0.385	0.854		
Trust in AI Agent	-0.008	0.081	-0.002	-0.055	0.504	-0.343	-0.316	0.878	
Adoption Intention	0.377	0.265	0.234	0.322	0.501	-0.073	-0.151	0.463	0.881

Each construct's √AVE (diagonal) exceeds its correlations with other constructs.

Table 4. Discriminant validity — Heterotrait-Monotrait ratio (HTMT).

Construct	PE	EE	SI	HM	PAC	PAR	PRC	TR	ADI
Performance Expectancy	—								
Effort Expectancy	0.384	—							
Social Influence	0.222	0.258	—						
Hedonic Motivation	0.362	0.201	0.250	—					
Perceived Agent Competence	0.283	0.245	0.182	0.262	—				
Perceived Autonomy Risk	0.155	0.145	0.333	0.241	0.093	—			
Privacy Concern	0.158	0.166	0.252	0.257	0.077	0.448	—		
Trust in AI Agent	0.044	0.094	0.031	0.065	0.566	0.394	0.356	—	
Adoption Intention	0.430	0.308	0.268	0.369	0.562	0.091	0.170	0.513	—

All HTMT values < 0.85, confirming discriminant validity.

4.2 Structural model and hypotheses

The model explains 48% of the variance in adoption intention and 38% in trust (Table 6). As hypothesised, performance expectancy (β=0.25), social influence (β=0.13) and hedonic motivation (β=0.22) significantly raise adoption intention; effort expectancy is weakly positive. Perceived agent competence is the dominant antecedent of trust (β=0.49), while perceived autonomy risk (β=-0.25) and privacy concern (β=-0.20) significantly reduce it. Trust strongly drives adoption (β=0.33) and partially mediates the competence and privacy-concern effects, which also act directly. All ten hypotheses are supported (Table 5, Figures 2–4).

Table 5. Structural model — hypothesis tests (bootstrap, 1,000 subsamples).

Hyp.	Path	β	t	p	f²	Decision
H1	Performance Expectancy → Adoption Intention	0.254	6.50	0.0000	0.088	Supported
H2	Effort Expectancy → Adoption Intention	0.082	2.14	0.0323	0.011	Supported
H3	Social Influence → Adoption Intention	0.133	3.50	0.0005	0.029	Supported
H4	Hedonic Motivation → Adoption Intention	0.224	5.52	0.0000	0.076	Supported
H5	Perceived Agent Competence → Trust in AI Agent	0.487	11.50	0.0000	—	Supported
H6	Perceived Autonomy Risk → Trust in AI Agent	-0.252	5.74	0.0000	—	Supported
H7	Privacy Concern → Trust in AI Agent	-0.200	4.33	0.0000	—	Supported
H8	Trust in AI Agent → Adoption Intention	0.331	7.95	0.0000	0.137	Supported

H9	Perceived Agent Competence → Adoption Intention	0.183	4.00	0.0001	0.039	Supported
H10	Privacy Concern → Adoption Intention	- 0.161	4.18	0.0000	0.038	Supported

*** p<.001, ** p<.01, * p<.05. f² effect sizes for predictors of Adoption Intention.

Table 6. Explanatory and predictive power

Construct	R^2	Q^2 (predictive relevance)
Trust in AI Agent	0.382	0.371
Adoption Intention	0.480	0.464

$Q^2 > 0$ for both endogenous constructs indicates predictive relevance. VIF values < 3.3 (no collinearity).

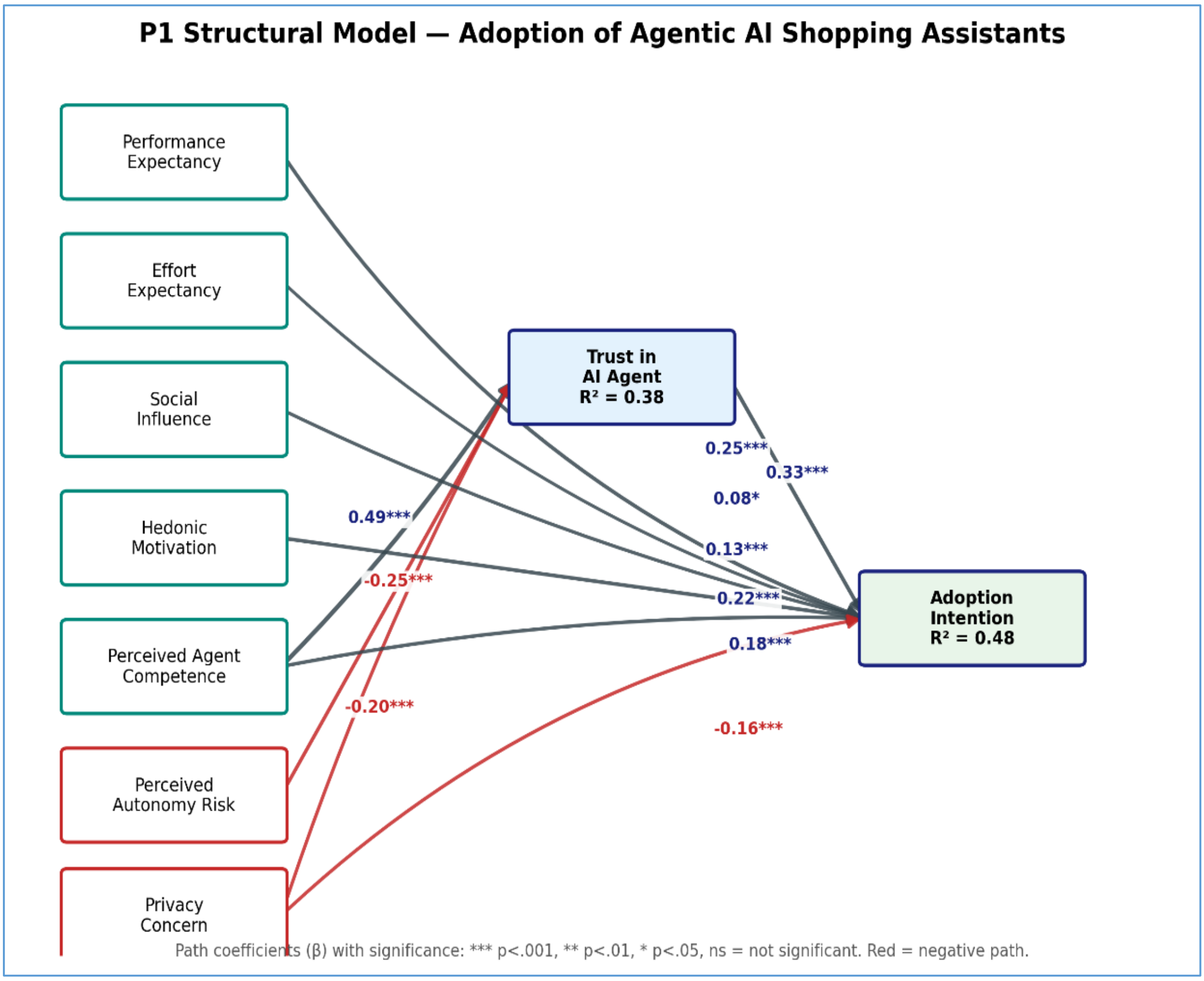

Figure 4. Estimated structural model — standardised path coefficients (β) with significance; negative paths in red (Adoption Intention $R^2 = 0.48$, Trust $R^2 = 0.38$).

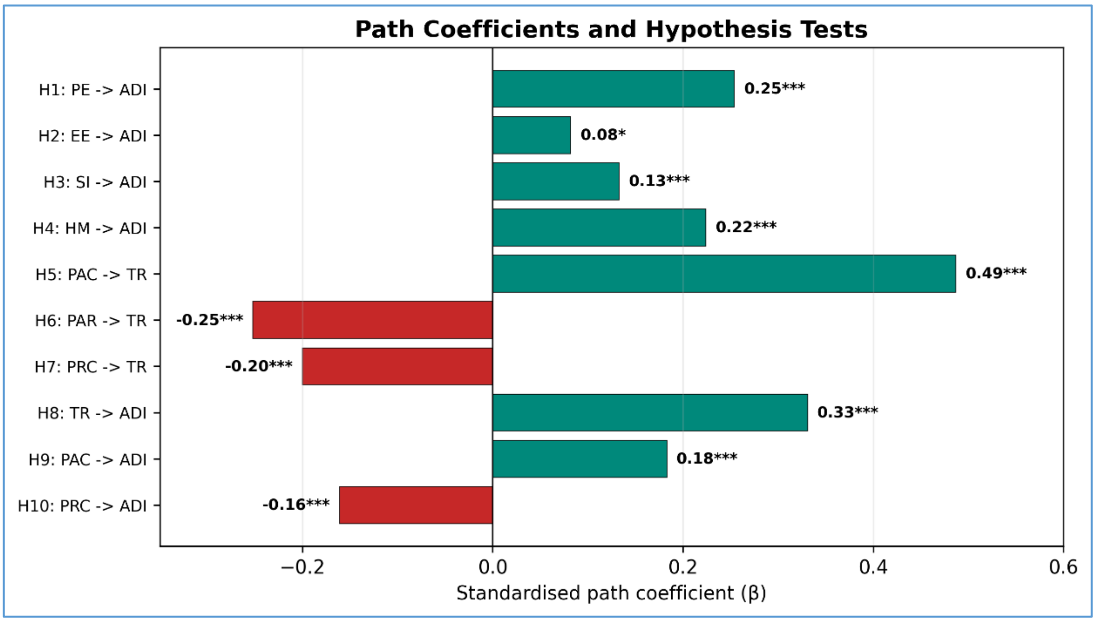

Figure 5. Standardised path coefficients and hypothesis outcomes.

Figure 5 presents the standardized path coefficients and hypothesis testing results. All of the proposed hypotheses are supported. Perceived agent competence is the most salient positive predictor for trust (0.49), whereas three negative predictors for trust include perceived autonomy risk (0.25) and privacy concern (0.20). Trust shows a positive effect on adoption intention (0.33), which is greater than performance expectancy, hedonic motivation, social influence, and effort expectancy. Our result proves that trust is an especially important factor for consumers' intention to adopt agentic AI shopping assistants.

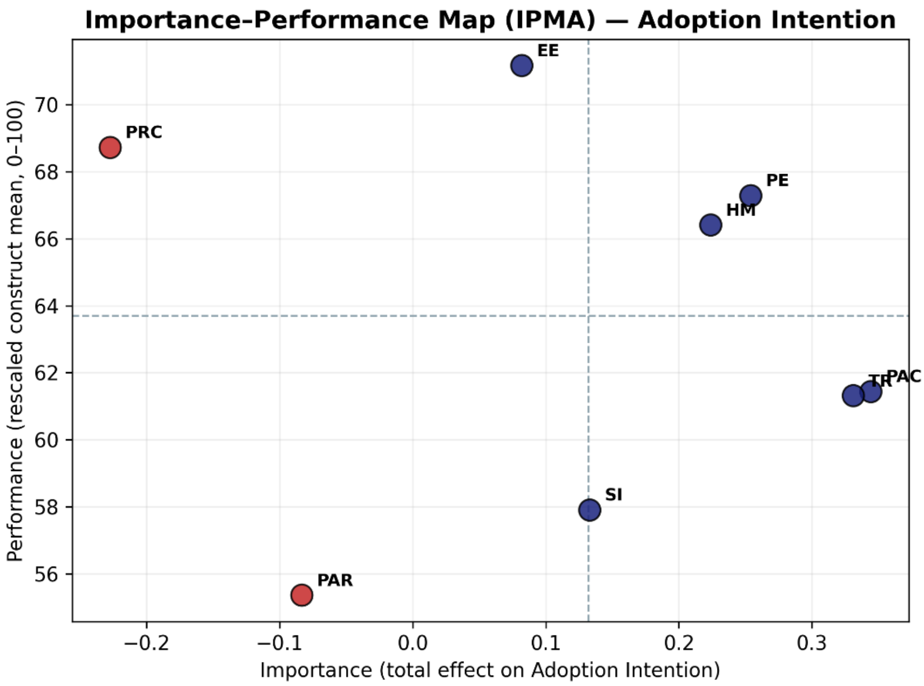

Figure 6. Importance–Performance Map for Adoption Intention.

The importance–performance map (Figure 6) shows perceived competence and trust combine high importance with moderate performance—the priority levers—whereas privacy concern exerts a strong negative pull that managers must neutralise.

5. Discussion

The study extends UTAUT2 to purchase-executing agentic AI and shows that classic adoption drivers are necessary but not sufficient: a trust mechanism, fed by agent-specific antecedents, is central. Perceived agent competence emerges as the strongest lever of trust, and trust is the principal conduit to adoption—evidence that delegating purchases is fundamentally a trust decision, not merely a usefulness calculation (closing G1–G3).

To drive adoption of AI shopping agents, marketers should (i) demonstrate agent competence visibly (transparent reasoning, track-record, accuracy guarantees), (ii) reduce perceived autonomy risk through user controls, spending limits and reversible actions, and (iii) address privacy concern with clear data-use disclosures and minimisation—because both significantly erode the trust on which adoption depends. Hedonic and social levers (enjoyable design, social proof) provide secondary boosts.

6. Limitations and Future Research

The study is cross-sectional and survey-based; longitudinal and behavioural data would strengthen causal claims. The sample is drawn from an online panel and a single market; replication across cultures and product categories is warranted. Respondents evaluated a described/illustrated agent rather than one used over time, so adoption intention—not actual behaviour—is the outcome. Future work could add objective usage, examine moderators such as product risk or consumer expertise, and compare advisory versus purchase-executing agents.

7. Conclusion

Agentic AI shopping assistants ask consumers to delegate not just search but the purchase itself. Across 412 consumers, this study shows adoption is driven less by convenience than by trust—built chiefly by perceived agent competence and eroded by autonomy risk and privacy concern—within an extended UTAUT2 frame that explains 48% of adoption intention. By identifying trust as the pivotal mechanism and competence and privacy as its key antecedents, the paper offers both a theoretical extension for agentic-AI adoption and a practical roadmap for marketers deploying purchase-executing agents.

Declarations

Data Availability

The anonymised survey dataset and analysis files are available from the corresponding author on reasonable request.

Funding

This research received no specific grant from any funding agency.

Conflicts of Interest

The authors declare no conflict of interest.

Ethics

Participants provided informed consent; responses were anonymous and voluntary, in line with institutional research-ethics guidelines.

References

1. Abdullah, M. F., Ibrahim, M. A., Bahtar, A. Z., & Khan, N. R. M. (2024). Conceptualizing the implications of artificial intelligence (AI) tools and personalization marketing on consumer purchase intention: Insights from the Malaysian e-commerce market. *Information Management and Business Review*, *16*(3), 430-436.

2. Bimaruci, H., Hudaya, A., & Ali, H. (2020). Model of consumer trust on travel agent online: analysis of perceived usefulness and security on re-purchase interests (case study tiket. com). *Dinasti International Journal of Economics, Finance & Accounting*, *1*(1), 110-124.
3. Chauhan, V., Yadav, R., & Choudhary, V. (2019). Analyzing the impact of consumer innovativeness and perceived risk in internet banking adoption: A study of Indian consumers. *International Journal of Bank Marketing*, *37*(1), 323-339.
4. De Bellis, E., & Johar, G. V. (2020). Autonomous shopping systems: Identifying and overcoming barriers to consumer adoption. *Journal of Retailing*, *96*(1), 74-87.
5. Dhiman, N., Arora, N., Dogra, N., & Gupta, A. (2020). Consumer adoption of smartphone fitness apps: an extended UTAUT2 perspective. *Journal of Indian Business Research*, *12*(3), 363-388.
6. Frank, D. A., Jacobsen, L. F., Søndergaard, H. A., & Otterbring, T. (2023). In companies we trust: consumer adoption of artificial intelligence services and the role of trust in companies and AI autonomy. *Information Technology & People*, *36*(8), 155-173.
7. Hou, Y. T. Y., & Jung, M. F. (2021). Who is the expert? Reconciling algorithm aversion and algorithm appreciation in AI-supported decision making. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1-25.
8. Alsharo, M., Alnsour, Y., Tarhini, A., & Eleimat, D. A. (2026). The prevalence of mobile wallets in developing countries: a retailers' perspective. *Review of International Business and Strategy*, *36*(1), 174-199.
9. Leffrang, D., Bösch, K., & Müller, O. (2023). Do people recover from algorithm aversion? An experimental study of algorithm aversion over time.
10. Luo, L. (2024). The impact of artificial intelligence and consumer behavior interaction on corporate brand management and marketing strategies. *Applied Mathematics and Nonlinear Sciences*, *9*(1), 1-17.
11. Ma, L. (2021). Understanding non-adopters' intention to use internet pharmacy: Revisiting the roles of trustworthiness, perceived risk and consumer traits. *Journal of Engineering and Technology Management*, *59*, 101613.
12. Mustafa, S., Zhang, W., Anwar, S., Jamil, K., & Rana, S. (2022). An integrated model of UTAUT2 to understand consumers' 5G technology acceptance using SEM-ANN approach. *Scientific Reports*, *12*(1), 20056.
13. O'Higgins, B., & Fatorachian, H. (2025). Consumer trust in artificial intelligence in the UK and Ireland's personal care and cosmetics sector. *Cogent Business & Management*, *12*(1), 2469765.
14. Penney, E. K., Agyei, J., Boadi, E. K., Abrokwah, E., & Ofori-Boafo, R. (2021). Understanding factors that influence consumer intention to use mobile money services: An application of UTAUT2 with perceived risk and trust. *Sage Open*, *11*(3), 21582440211023188.
15. Sritong, C., Sawangproh, W., & Teangsompong, T. (2024). Unveiling the adoption of metaverse technology in Bangkok metropolitan areas: a UTAUT2 perspective with social media marketing and consumer engagement. *PLoS One*, *19*(6), e0304496.
16. Toukabri, M., & Boutaleb, B. (2025). Assessing factors impacting electric vehicle adoption in Saudi Arabia: Insights on willingness to pay, environmental awareness, and perceived risk. *Engineering, Technology & Applied Science Research*, *15*(1), 19729-19736.
17. Chen, J., Shi, J., Gan, L., Zhang, J., Zhang, Q., Zhang, D., ... & Yinghui, X. (2025, July). AI2Agent: An End-to-End Framework for Deploying AI Projects as Autonomous Agents. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 3: System Demonstrations)* (pp. 535-541).

18. Yu, A., Lebedev, E., Everett, L., Chen, X., & Chen, T. (2025). Autonomous Deep Agent. *arXiv preprint arXiv:2502.07056*.
19. Yang, Y., Chai, H., Shao, S., Song, Y., Qi, S., Rui, R., & Zhang, W. (2026). Agentnet: Decentralized evolutionary coordination for llm-based multi-agent systems. *Advances in Neural Information Processing Systems*, *38*, 107309-107336.
20. Sharma, R., de Vos, M., Chari, P., Raskar, R., & Kermarrec, A. M. (2025). Collaborative agentic AI needs interoperability across ecosystems. *arXiv preprint arXiv:2505.21550*.
21. Zhang, Y., Lin, C., Tang, S., Chen, H., Zhou, S., Ma, Y., & Tresp, V. (2025, November). Swarmagentic: Towards fully automated agentic system generation via swarm intelligence. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing* (pp. 1778-1818).
22. Derouiche, H., Brahmi, Z., & Mazeni, H. (2025). Agentic ai frameworks: Architectures, protocols, and design challenges. *arXiv preprint arXiv:2508.10146*.
23. Allouah, A., Besbes, O., Figueroa, J. D., Kanoria, Y., & Kumar, A. (2026, April). What Is Your AI Agent Buying? Evaluation, Biases, Model Dependence, & Emerging Implications of Agentic E-Commerce. In *Proceedings of the ACM Web Conference 2026* (pp. 8697-8700).
24. Jin, X., & Li, J. (2025). The Influence of ‘Algorithm Aversion’and ‘Algorithm Appreciation’Among Consumers in Unstructured Tasks. *International Journal of Consumer Studies*, *49*(6), e70133.
25. Abu-Dalbouh, H. M., Freihat, M. M., Jawarneh, R. I., Elhadi, O. A. M., Elimam, M. I., Abalkhail, L. S. A., ... & Alateyah, S. A. (2026). Improving Decision-Making Processes in Retail Through Artificial Intelligence for Advanced Management Information Systems: A Study on Consumer Behavior in Qassim. *International Journal of Advanced Computer Science & Applications*, *17*(3), 235.
26. Wang, S., Wang, J., Li, J., Wang, J., & Liang, L. (2018). Policy implications for promoting the adoption of electric vehicles: do consumer’s knowledge, perceived risk and financial incentive policy matter?. *Transportation Research Part A: Policy and Practice*, *117*, 58-69.
27. Zhao, Z. (2024). The interaction of consumer behavior and artificial intelligence technologies: New trends in marketing. Frontiers in Business, Economics and
28. Khairia A H Sehib, Husniyah Abdullah Mohammed, & Salha Muftah Abdulqader Ahwaiti. (2025). An Economic Study of the Consumption Expenditure Function on White Meat (A Case Study of Al-Bayda Municipality). Journal of Libyan Academy Bani Walid, 1(4), 177–184. https://doi.org/10.61952/jlabw.v1i4.345
29. Faida Ahmed Salem Saeed. (2026). The effectiveness of monetary policy in containing inflation in light of digital transformation: A comparative analytical study between Libya, Algeria, and the UAE during the period (2020-2025). Journal of Libyan Academy Bani Walid, 2(1), 378–394. https://doi.org/10.61952/jlabw.v2i1.481
30. Ghada Moftah Soufeljin, & Hudaa Ali Farhoud. (2025). The Impact of Clothing Care Labels on Purchase Behavior Among Women in Libya: A Case Study. Journal of Libyan Academy Bani Walid, 1(3), 403–416. https://doi.org/10.61952/jlabw.v1i3.238

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.