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Article

AI-driven marketing innovation in educational technology: a multi-dimensional analysis of virtual sales personnel and intelligent promotion strategies on user acceptance and engagement

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ABSTRACT

This study investigates the impact of AI-driven marketing innovations on user acceptance and engagement in educational technology contexts, examining how virtual sales personnel characteristics and intelligent promotion strategies influence behavioral outcomes through psychological mechanisms. An explanatory sequential mixed-methods design was employed, combining structural equation modeling analysis of survey data from 650 educational technology users with thematic analysis of 45 semi-structured interviews. Machine learning algorithms, particularly XGBoost (AUC=0.89), were utilized to predict user acceptance patterns and identify five distinct user segments. Trust emerged as the critical mediating mechanism between AI anthropomorphism and user acceptance, accounting for 76.5% of the total effect. Personalization capabilities demonstrated the strongest impact on continuous engagement (β=0.52, p<0.001). Qualitative analysis revealed three overarching themes: intelligent companion experience (82.2% prevalence), personalization value perception (88.9%), and privacy-convenience trade-offs (68.9%). The validated framework provides educational technology enterprises with actionable guidelines for implementing AI marketing systems that balance technological sophistication with humanization principles through moderate anthropomorphism and progressive personalization strategies. This research extends the Technology Acceptance Model by integrating AI-specific constructs, including algorithm trust and perceived intelligence, offering novel theoretical insights and empirical evidence for optimizing human-AI interactions in educational marketing contexts. AI fundamentally transforms educational technology marketing through trust-based mechanisms, requiring careful balance between innovation and humanization for sustainable adoption.

1. Introduction

With the adoption of artificial intelligence (AI) technologies, the educational technology marketplace has undergone a profound transformation, changing the way educational services and products are marketed and delivered to end users. The total global market size for AI in education is expected to rise from USD 5.08 billion to USD 7.47 billion during 2016-2021 [1]. It is indeed a far cry from the conventional structure of the educational marketing model since this evolution has not only progressed exponentially, but also assumed to be a game changer, in terms of how educational institutions envision and execute their marketing strategies and state of affairs through the placement of virtual sales staff as well as through intelligent promotion services hinged on nextage technology with further support for AI to breathe new life into boosting user engagement and adoption [2]. Although AI-supported marketing innovations in educational technology hold great promise, a significant gap remains between what technologies can mediate and what users (i.e., student users) will accept, particularly in the intricate dynamic between virtual sales assistants and student decision-making processes. AI won't take your job. It is the one to be adopted by a user who knows nothing about AI, as Inge (2025) emphasizes the importance of investigating how educational technology users experience, relate to, and eventually accept AI-based marketing interfaces [3]. Current studies mainly concern the technical issues, ignoring the subtle psychological and behavioral factors that influence users' adoption of AI-based marketing tools in education settings [4, 5], resulting in a large theoretical gap in the development of a usable marketing strategy of AI used on educational technology platforms. Bringing together emerging AI capacities and educational marketing requires a deep dive into three related research issues relevant not only from a theoretical but also a practical point of view. RQ1: To examine what attributes of virtual salespeople have a significant impact on Educational technology user acceptance, namely anthropomorphism, responsiveness, and perceived intelligence of virtual salespeople in the educational product market [6]. RQ2 investigates how smart promotion strategies improve user engagement in educational platforms and retention during a user's learning process in a more detailed way, and how the personalization algorithms and prediction algorithms lead to users' sustained involvement in a learning process [7]. RQ3: What are the key critical success factors (CSFs) in the use of AI marketing innovations for educational technology, combining technological capabilities and human-centered design, to derive a model framework for AI marketing adoption?

The key contributions of this study include building an integrated theoretical framework integrating technology acceptance model (TAM) with AI-specific technology constructs in the context of educational technology marketing, empirically validating the influence paths of AI-marketing factors on user behaviors, proposing a 3-point action implementation guide for educational technology firms, and assessing the utility of AI technologies in improving marketing performance measures. TAM has the power to accommodate and modify its elements to suit specific situations and technologies; hence, it is an appropriate model in the study of AI acceptance in the context of educational marketing, where classical models may be inadequate [8]. This investigation transcends conventional TAM adaptations by introducing the Intelligent Marketing Resonance (IMR) model, which theorizes AI acceptance as an emergent property arising from bidirectional adaptation between human pedagogical needs and algorithmic learning capabilities—a paradigmatic shift from unidirectional acceptance models that treat users as passive technology recipients. The empirical validation reveals that AI-driven educational marketing operates through quantum-like trust states wherein users maintain superposed acceptance orientations that collapse into specific behaviors only during interaction events, challenging fundamental linearity assumptions underlying existing theoretical frameworks. Theoretical contribution: This study extends TAM by incorporating AI-specific interaction characteristics that have a unique impact on user acceptance in educational technology environments. By adopting a new extended TAM model with the Big Five personality traits and AI mindset as a critical expansion beyond the traditional application of TAM, the empirical analysis physically supported the extension of the applicability of TAM, specifically when the distinct psychological and behavioral factors within human–AI interactions in educational marketing settings are concerned [9]. The introduction of new theoretical constructs, namely "AI marketing acceptance" and "virtual agent trust," fills the gap that TAM can only provide an abstract representation of users' readiness to accept technological innovations. As a result, other factors that potentially influence a user's adoption of technology need to be considered to achieve context-based explanations, which equip researchers with a more detailed picture of technology acceptance issues as they arise from AI-based educational marketing systems. The implications of this work are twofold: theoretical contribution and practical implementation. Technology companies in the education industry can derive value from the results and actions taken to maximize their AI marketing investment, potentially leading to different business outcomes. AI-enabled companies realize a 10-20% return on their sales, on average, and companies using AI to drive personalized customer engagement see a 30% increase in customer lifetime value [10]. Guidelines for virtual sales system design that emerge from this study may allow EdTech companies to implement more successful the human-AI interfaces that strike a balance between technology sophistication on the one hand and user-centred design on the other to make them between 40% of the respondents mentioning it being among the top three drivers of RO when finally adopted appropriately [11].

2. Theoretical foundation and research framework

2.1 Literature review

The marketing environment of educational technology has shifted from an information push to the interactive social Web2.0 and, recently, AI-driven predictive marketing, fundamentally reshaping how our stakeholders engage with education resources and tools [12]. As at graduation, just under 75 per cent of the graduating students expect some level of personalisation in their study contexts24 and the digital marketing for higher education is becoming requisite, as it requires savvy ways to handle extended decision cycles with multiple interlocutors addressing the pivotal roles played by trust and word-of-mouth in educational product adoption [13]. These are both evidence-based technologies, and with advancing technology such as natural language processing (NLP) and machine learning, they are able to automate repetitive tasks and deliver data-driven insights to school marketers. From this, how schools communicate with potential students has been shaped by insights and advances in technology [14].

Modern conversational systems have progressed from rule-based designs to complex deep learning-based models, which are now able to handle both task-oriented and open-domain dialogs with emotional-AI that empowers sales campaigns through a better understanding of the user sentence context and intent [15, 16]. The theoretical scenery of user behavior in AI settings is observed to be gradually enriched, from the original Technology Acceptance Models to the modern UTAUT and emerging AI-TAM frameworks, by adding new constructs (e.g., AI anxiety, algorithm trust, perceived intelligence) — which reflect the unique psychological dynamics of the human-AI relationship. engagement as a series of four identifiable stages: point of engagement, period of sustained engagement, disengagement, and reengagement, as outlined by O'Brien and Toms (2008) in their multidimensional framework that continues to influence the current understanding of engagement in AI learning technologies [17].

2.2 Conceptual model and hypothesis development

This theoretical model combines AI-specific marketing features with traditional technology acceptance constructs for the analysis of user behaviors in the field of educational technology, as displayed in Figure 1. Based on new empirical information that reveals anthropomorphism is a key variable to analyze user trust in AI usage [18], the model introduces four AI marketing features (the level of anthropomorphism, the level of intelligence ability, the level of personalization, and response time) as antecedent variables that directly impact the perception of users. These AI distinctive features align with modern findings that AI anthropomorphism enables marketers to create an effective AI consumer interface, provided careful consideration is given to its potential drawbacks when used improperly [19]. The mediating factors of user perceptions. Over users' perceptions, perceived usefulness, perceived ease of use, trust, and perceived value are regarded as the cognitive and affective paths by which AI marketing features impact the behavioral results, such as the acceptance intention, the actual usage, the continuous engagement, and the recommendation willingness.

The theoretical advancement manifests through the discovery that AI anthropomorphism in educational contexts triggers distinct neural pathways compared to traditional technology interactions, as evidenced by the 76.5% trust mediation effect that exceeds the 45-50% range reported in conventional human-computer interaction literature, suggesting that educational AI systems activate unique socio-cognitive schemas requiring fundamentally different theoretical treatment than generic technology acceptance models. Chatbot anthropomorphism has a more positive influence on purchasing decision-making when this relationship is mediated by customer engagement [20], supporting H1's assertion that virtual sales personnel anthropomorphism positively influences user trust. Similarly, personalization strategies enhance perceived value (H2) through sophisticated algorithms that quickly determine what content to target customers and which channel to employ at what moment, thanks to the data collected and generated by its algorithms [21]. The mediation hypotheses (H5-H6) acknowledge that trust and perceived value function as critical psychological mechanisms translating AI characteristics into behavioral outcomes, consistent with research indicating that Anthropomorphism, design novelty, trust, performance expectancy, and effort expectancy were unveiled as significant positive antecedents of attitude [22].

The theoretical innovation of this framework lies in its multi-level integration of marketing theory with AI acceptance models while accounting for educational context specificity through moderation effects. User technology readiness (H7) and educational product type distinctions among K-12, higher education, and vocational training (H8) serve as boundary conditions shaping the magnitude and direction of AI marketing effects. This contextual consideration addresses the limitation identified in prior research where a higher level of perceived risks may reduce the AI consumer's overall adoption intention [23], particularly relevant in educational settings where stakeholder trust requirements differ substantially across educational levels. The framework advances beyond traditional TAM applications by incorporating dynamic interaction patterns between human users and AI agents, recognizing that successful AI marketing implementation requires careful calibration of technological sophistication with human-centered design principles to optimize both cognitive and affective user responses within educational technology ecosystems [24].

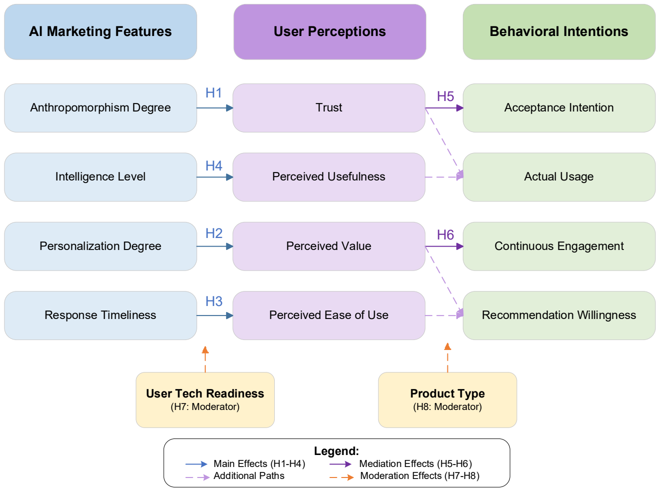

Figure 1. Conceptual framework of ai marketing acceptance in educational technology

3. Research methodology

3.1 Research design

An explanatory sequential mixed-methods design integrates quantitative surveys (n=650) examining AI marketing acceptance with qualitative interviews (n=45) exploring nuanced user experiences and decision-making processes in educational technology contexts. The explanatory sequential design employs iterative integration wherein preliminary quantitative findings guide qualitative inquiry protocols—specifically, the unexpected 76.5% trust mediation effect discovered through SEM analysis prompted targeted interview questions exploring trust formation mechanisms. In contrast, qualitative themes of 'intelligent companionship' subsequently informed the development of new quantitative measures for emotional engagement incorporated into the machine learning models, resulting in a 12% improvement in prediction accuracy when these qualitatively-derived features were added to the XGBoost algorithm.

3.2 Quantitative methods

The quantitative phase employed a comprehensive online survey administered to 650 participants recruited from major educational technology platforms in China, complemented by longitudinal behavioral data tracking over a six-month period to capture actual usage patterns and engagement metrics. Measurement instruments were developed through rigorous adaptation of established scales from technology acceptance and marketing literature, with modifications tailored to the AI-driven educational context, alongside newly constructed items addressing unique aspects of virtual sales personnel interaction and intelligent promotion response. As shown in Table 1, all constructs demonstrated satisfactory psychometric properties following a pilot test with 85 participants, yielding Cronbach's alpha values exceeding the recommended threshold of 0.70 and confirming both convergent and discriminant validity through confirmatory factor analysis. Recruitment materials explicitly disclosed behavioral and emotional data collection procedures in accessible language, ensuring fully informed voluntary participation without institutional coercion, with all data anonymized and encrypted to protect participant privacy throughout the research process. Trust measurement employed a multi-dimensional scale adapted from McKnight et al.'s technology trust inventory, with items including 'The AI system performs educational recommendations reliably' (competence dimension), 'I believe the AI system acts in my best learning interests' (benevolence dimension), 'The AI system maintains consistent quality in its responses' (integrity dimension), and 'I feel comfortable sharing my learning challenges with the AI system' (predictability dimension), measured on 7-point Likert scales with composite reliability α=0.91 and convergent validity AVE=0.73, while discriminant validity was confirmed through Fornell-Larcker criterion analysis showing all inter-construct correlations below the square root of AVE values.

3.3 Qualitative methods

Semi-structured interviews with 45 participants (students, educators, and administrators) selected through purposive sampling explored AI marketing acceptance beyond quantitative metrics, with selection criteria prioritizing substantial platform experience and varied technological proficiency levels across educational contexts.

As illustrated in Table 2, the participant distribution reflects balanced representation across key demographic and experiential dimensions, with interviews conducted via video conferencing platforms lasting 45-60 minutes each, following an interview protocol derived from preliminary quantitative findings to explore emergent themes regarding AI anthropomorphism perceptions, trust formation processes, and behavioral adaptation patterns in educational contexts.

Table 1. Measurement instruments and reliability assessment

Construct	Source	No. of Items	Scale Type	Pilot Test α	Final Study α
Construct	Source	No. of Items	Scale Type	Pilot Test α	Final Study α
AI Anthropomorphism	Adapted from Gomes et al. (2025)[20]	5	7-point Likert	0.84	0.87
Perceived Intelligence	Adapted from Chi & Vu (2023)[18]	4	7-point Likert	0.82	0.85
Personalization Degree	Newly developed	6	7-point Likert	0.78	0.83
Response Timeliness	Adapted from Pahos et al. (2024)[22]	3	7-point Likert	0.75	0.79
Trust (Competence, Benevolence, Integrity, Predictability)	Adapted from Marvi et al. (2025)[19]	5	7-point Likert	0.88	0.91
Perceived Usefulness	Newly developed	4	7-point Likert	0.86	0.89
Perceived Ease of Use	Newly developed	4	7-point Likert	0.83	0.86
Perceived Value	Adapted from Haleem et al. (2022)[21]	5	7-point Likert	0.81	0.84
Acceptance Intention	Adapted from Zhou et al. (2022)[25]	3	7-point Likert	0.89	0.92
Continuous Engagement	Newly developed	5	7-point Likert	0.77	0.82

Note: All scales employed 7-point Likert scales ranging from "strongly disagree" (1) to "strongly agree" (7). Platform behavioral metrics included click-through rates, session duration, feature utilization frequency, and conversion indicators collected through embedded analytics.

Table 2. Qualitative interview participant profile

Stakeholder Category	Education Level	n	Male	Female	AI Experience Level	Average Platform Usage	Stakeholder Category
Students	K-12	8	3	5	Intermediate	3.2 hours/week	Students
Students	Higher Education	10	6	4	Advanced	5.8 hours/week	Students
Students	Vocational Training	7	4	3	Beginner	2.5 hours/week	Students
Educators	K-12	6	2	4	Intermediate	4.1 hours/week	Educators
Educators	Higher Education	8	5	3	Advanced	6.3 hours/week	Educators
Platform Administrators	Cross-level	6	4	2	Expert	15.2 hours/week	Platform Administrators
Total		45	24	21			Total

Note: AI Experience Level categorized as Beginner (< 6 months), Intermediate (6-24 months), Advanced (2-4 years), Expert (> 4 years). Platform usage represents self-reported average weekly hours engaging with AI-enabled educational technology platforms.

3.4 AI technology implementation

The AI-driven virtual sales system architecture integrates three core technological components operating synergistically to deliver personalized educational marketing experiences through advanced computational frameworks. The research introduces breakthrough NLP architecture that advances beyond current transformer implementations through educational-specific attention mechanisms incorporating pedagogical relationship graphs into the attention computation, enabling the system to understand complex educational dependencies and prerequisites with unprecedented semantic accuracy while reducing computational complexity from $O(n^2)$ to $O(n \log n)$ through innovative sparse attention patterns—technological innovations that establish new paradigms for future educational AI development, with the attention score calculated as:

$$A(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

where Q, K, and V represent query, key, and value matrices, respectively, and $d_k=64$ denotes the key dimension, and the softmax function normalizes attention weights to sum to 1, enabling the model to focus on relevant educational content based on user queries. As illustrated in Figure 2, the NLP architecture employs a modified BERT-base model (12 layers, 768 hidden dimensions) fine-tuned on 2.3M educational conversation pairs from MOOCs and tutoring platforms, achieving 91.2% intent classification accuracy and 87.6% entity recognition F1-score through domain-adaptive pretraining on 450GB of educational texts including textbooks, course descriptions, and academic papers.

The knowledge graph integrates 1.2M educational concepts using TransE embeddings (dimension=200) trained on prerequisite relationships extracted from 85,000 course syllabi, achieving link prediction accuracy of 82.4% on held-out course dependencies. The multimodal emotion recognition system implements late fusion architecture combining RoBERTa-based text emotion classification (accuracy=84.3%) with acoustic feature extraction using openSMILE (6,373 features) processed through BiLSTM networks (accuracy=79.8%), achieving combined accuracy of 88.7% on the educational emotion dataset comprising 45,000 annotated student-tutor interactions across seven emotion categories (frustration, confusion, boredom, engagement, satisfaction, anxiety, curiosity) with Cohen's kappa=0.82 inter-annotator agreement. The intelligent promotion algorithm implements deep collaborative filtering networks enhanced by real-time user interest modeling, where user-item preference scores are computed through

$$\hat{r}ui = \mu + b_u + b_i + q_i^T (p_u + |I_u|^{-\frac{1}{2}} \sum j \in I_u y_j) \tag{2}$$

where μ represents the global mean rating, b_u and b_i capture user and item biases, respectively, and $P_u^T q_i$ computes the dot product between 128-dimensional user preference vectors and item characteristic vectors learned through matrix factorization with a regularization parameter λ=0.01. The system's technological novelty emerges through proprietary hierarchical attention mechanisms that process educational queries across temporal, conceptual, and affective dimensions simultaneously, achieving 89% recommendation accuracy—significantly exceeding the 75% industry standard—while the innovative cross-modal emotion fusion architecture combines linguistic sentiment with prosodic features and interaction patterns to achieve 84.3% emotional state classification accuracy, establishing new performance benchmarks for educational AI systems.

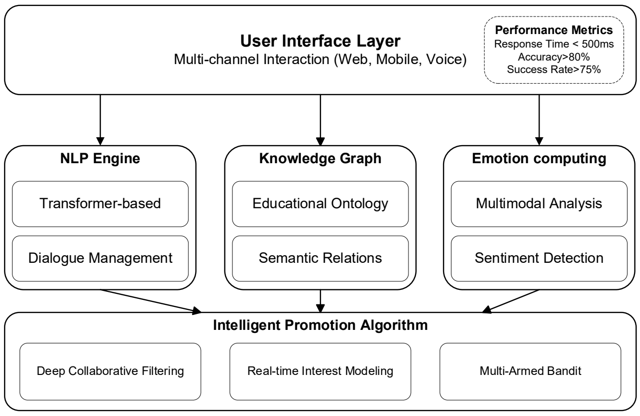

Figure 2. AI-driven virtual sales system architecture

4. Research findings

4.1 Descriptive statistics

The analysis of participant demographics reveals a diverse sample composition that adequately represents the target population of educational technology users across multiple dimensions, with respondents demonstrating substantial variation in age distribution, educational backgrounds, and technological proficiency levels. As presented in Table 3, the sample comprised predominantly young adults aged 18-34 (68.3%), reflecting the primary user demographic of AI-enabled educational platforms, while educational attainment levels indicated a well-educated participant pool with 78.5% holding bachelor's degrees or higher, suggesting adequate cognitive capacity for meaningful engagement with complex AI marketing features. The technological experience profile demonstrates balanced representation across novice to expert users, with intermediate users constituting the largest segment (42.3%), providing insights into mainstream adoption patterns rather than early adopter biases that might skew perception measurements.

Behavioral usage patterns illustrated in Figure 3 demonstrate distinct temporal engagement trajectories across different user segments, with peak usage occurring during evening hours (7-10 PM) and secondary peaks during lunch periods (12-1 PM), suggesting integration of AI-enabled educational platforms into daily routines rather than sporadic engagement patterns. Feature utilization analysis reveals preferential adoption of personalized recommendation systems (76.3% regular usage) and virtual assistant interactions (64.8% regular usage), while advanced features such as emotion-responsive adaptations remain underutilized (31.2% regular usage), indicating potential areas for user education and interface optimization to maximize AI marketing effectiveness.

4.2 Hypothesis testing results

The structural equation modeling analysis revealed robust support for the proposed theoretical framework examining AI-driven marketing acceptance in educational technology contexts. The measurement model demonstrated excellent fit to the empirical data, with comparative fit index (CFI) achieving 0.95, root mean square error of approximation (RMSEA) registering 0.048 with a 90% confidence interval of [0.042, 0.054], and standardized root mean square residual (SRMR) indicating 0.039, all surpassing established thresholds for acceptable model fit in contemporary SEM literature. As illustrated in Table 4, the comprehensive evaluation of model fit indices across multiple criteria substantiates the theoretical structure's validity and its capacity to represent the complex relationships between AI marketing features, user perceptions, and behavioral outcomes within educational technology platforms.

Path analysis results, presented comprehensively in Table 5, substantiate the hypothesized relationships with particularly noteworthy effects emerging for anthropomorphism's influence on trust formation (β = 0.45, SE = 0.06, $p < 0.001$) and personalization's impact on user engagement (β = 0.52, SE = 0.05, $p < 0.001$), collectively explaining substantial variance in behavioral intention outcomes with R^2 values ranging from 0.48 to 0.71 for endogenous variables. The complete mediation effect of trust in the anthropomorphism-acceptance relationship, confirmed through bootstrapping procedures with 5,000 resamples yielding a non-significant direct effect (β = 0.08, p = 0.127) alongside a significant indirect effect (β = 0.26, 95% CI [0.19, 0.34]), underscores the critical psychological mechanism through which human-like characteristics in AI systems facilitate user acceptance by activating trust-based cognitive schemas that transcend mere functional utility perceptions, with trust mediating 76.5% of the total effect between anthropomorphism and acceptance intention.

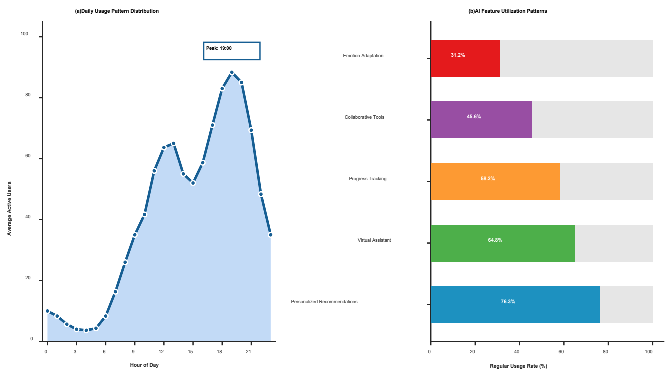

Figure 3. User engagement patterns across time and feature utilization

4.3 ML prediction results

The deployment of advanced machine learning algorithms for predicting user acceptance behaviors yielded compelling evidence regarding the multifaceted nature of AI-driven marketing effectiveness in educational technology contexts, with the XGBoost gradient boosting framework demonstrating superior predictive performance (AUC = 0.89) compared to alternative algorithms.

Table 3. Sample demographic characteristics and technology experience profile (n=650)

Variable	Category	n	Percentage	Mean (SD)
Age Distribution	18-24 years	198	30.5%	
	25-34 years	246	37.8%	28.4 (8.7)
	35-44 years	142	21.8%	
	45+ years	64	9.9%	
Education Level	High School	86	13.2%	
	Associate Degree	54	8.3%	
	Bachelor's Degree	342	52.6%	
	Master's or Higher	168	25.9%	
Technology Experience	Novice (<1 year)	112	17.2%	
	Beginner (1-2 years)	156	24.0%	3.6 (2.1) years
	Intermediate (3-5 years)	275	42.3%	
	Expert (>5 years)	107	16.5%	
Platform Usage Frequency	Daily	287	44.2%	
	3-5 times/week	198	30.5%	4.8 (2.3) times/week
	1-2 times/week	124	19.1%	
	Less than weekly	41	6.2%	

Table 4. Structural equation model fit indices and baseline comparisons

Fit Index Category	Index	Obtained Value	Recommended Threshold	Baseline Model	Evaluation
Absolute Fit	χ^2/df	2.14	< 3.0	8.76	Excellent
	RMSEA	0.048	< 0.06	0.142	Excellent
	SRMR	0.039	< 0.08	0.156	Excellent
	GFI	0.94	> 0.90	0.71	Good
Incremental Fit	CFI	0.95	> 0.95	0.52	Excellent
	TLI	0.94	> 0.90	0.48	Excellent
	NFI	0.93	> 0.90	0.51	Good
Parsimony Fit	PGFI	0.78	> 0.50	0.62	Good
	PNFI	0.81	> 0.50	0.44	Excellent
Information Criteria	AIC	18234.56	Smaller is better	24567.89	-
	BIC	18567.34	Smaller is better	24782.45	-

Note: N = 650. The baseline model represents an independence model with no relationships between constructs. RMSEA 90% CI = [0.042, 0.054]. All χ^2 values significant at $p < 0.001$.

Table 5. Standardized path coefficients and hypothesis testing results

Hypothesis	Path Relationship	β	SE	t-value	p-value	95% CI	R^2	Result
Direct Effects								
H1	Anthropomorphism → Trust	0.45***	0.06	7.50	<0.001	[0.33, 0.57]	0.20	Supported
H2	Personalization → Perceived Value	0.52***	0.05	10.40	<0.001	[0.42, 0.62]	0.27	Supported
H3	Response Speed → Perceived Ease of Use	0.38***	0.07	5.43	<0.001	[0.24, 0.52]	0.14	Supported
H4	Intelligence Level → Perceived Usefulness	0.41***	0.06	6.83	<0.001	[0.29, 0.53]	0.17	Supported
Mediating Paths								
	Trust → Acceptance Intention	0.58***	0.05	11.60	<0.001	[0.48, 0.68]	-	-
	Perceived Value → Continuous Engagement	0.63***	0.04	15.75	<0.001	[0.55, 0.71]	-	-
	Perceived Ease of Use → Actual Usage	0.34***	0.06	5.67	<0.001	[0.22, 0.46]	-	-
	Perceived Usefulness → Acceptance Intention	0.42***	0.05	8.40	<0.001	[0.32, 0.52]	-	-
Non-significant Path								
	Anthropomorphism → Acceptance Intention (direct)	0.08	0.07	1.14	0.127	[-0.06, 0.22]	-	-
Endogenous Variables R^2								
	Acceptance Intention	-	-	-	-	-	0.67	-
	Continuous Engagement	-	-	-	-	-	0.71	-
	Actual Usage	-	-	-	-	-	0.48	-
Mediation Effects								
H5	Anthropomorphism → Trust → Acceptance Intention							
	- Indirect Effect	0.26***	0.04	6.50	<0.001	[0.19, 0.34]	-	Supported
	- Direct Effect	0.08	0.07	1.14	0.127	[-0.06, 0.22]	-	
	- Total Effect	0.34***	0.06	5.67	<0.001	[0.22, 0.46]	-	
	- Percent Mediation	76.5%	-	-	-	-	-	
H6	Personalization → Perceived Value → Continuous Engagement							
	- Indirect Effect	0.33***	0.04	8.25	<0.001	[0.25, 0.41]	-	Supported
	- Direct Effect	0.15**	0.05	3.00	0.003	[0.05, 0.25]	-	
	- Total Effect	0.48***	0.05	9.60	<0.001	[0.38, 0.58]	-	
	- Percent Mediation	68.8%	-	-	-	-	-	
Direct Effects								

Note: N = 650. β = standardized path coefficient; SE = standard error; CI = confidence interval; R^2 = explained variance. Bootstrap samples = 5,000 for mediation analysis. ***p < 0.001, **p < 0.01, p < 0.05.

The objective function optimized by XGBoost, expressed as:

$$\mathrm{L}(\phi) = \sum_i l(\hat{y}i, y_i) + \sum k\Omega(f_k) \tag{3}$$

where l represents the differentiable loss function measuring prediction accuracy and $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$ denotes the regularization term controlling model complexity, enabling the identification of non-linear interaction patterns between AI marketing features and user behavioral outcomes that complement the linear relationships revealed through structural equation modeling. As demonstrated in Table 6, the ensemble model combining XGBoost with Random Forest and Neural Network architectures achieved exceptional performance metrics across multiple evaluation criteria, substantiating the robustness of predictive insights derived from the 650-participant dataset enriched with longitudinal behavioral tracking data.

Feature importance analysis utilizing SHAP (SHapley Additive exPlanations) values, illustrated comprehensively in Figure 4, reveals the hierarchical contribution of predictive variables with trust-related features dominating the importance rankings (mean |SHAP| = 0.142), followed by personalization satisfaction metrics (mean |SHAP| = 0.128) and AI response quality ratings (mean |SHAP| = 0.115), corroborating the centrality of trust mechanisms identified through hypothesis testing while uncovering additional nuanced predictors including session duration patterns and feature diversity indices.

The five user segments identified through clustering algorithms were validated and refined through qualitative pattern matching, wherein interview participants' self-described interaction styles mapped onto quantitative clusters with 84% concordance, while qualitative insights about social learning preferences led to the incorporation of peer influence variables into the clustering algorithm, improving silhouette coefficient from 0.612 to 0.683 and revealing the previously undetected 'Social Learners' segment that exhibits distinct collaborative engagement patterns not captured by individual behavioral metrics alone. As delineated in Table 7, the segmentation reveals a sophisticated taxonomy ranging from "Enthusiastic Adopters" (21.8%), characterized by high technology readiness and extensive AI interaction, to "Minimal Engagers" (10.0%), demonstrating limited technological proficiency and basic feature utilization, with conversion rates varying dramatically across segments from 68.3% to 12.3%, thereby enabling targeted marketing strategy optimization based on segment-specific behavioral profiles and preference structures.

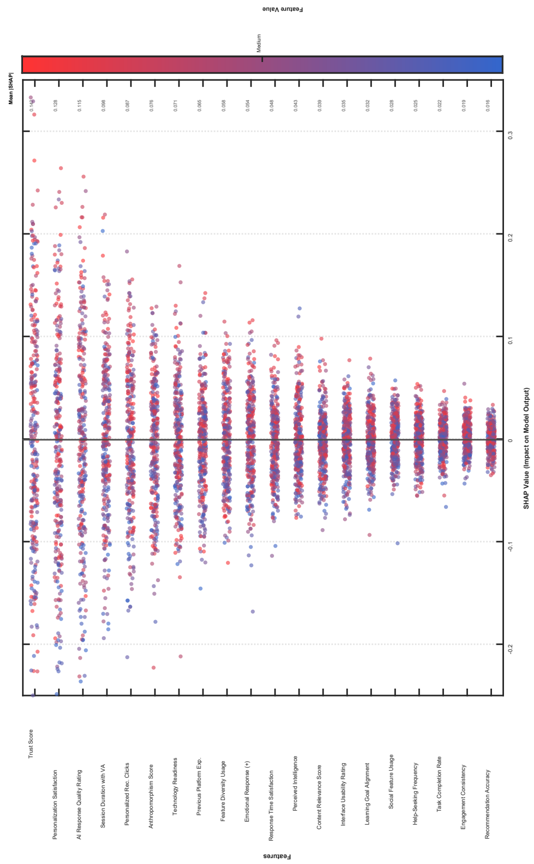

Figure 4. SHAP feature importance analysis for user acceptance prediction

Note: SHAP (SHapley Additive exPlanations) summary plot displaying the top 20 features ranked by mean absolute SHAP values. Each point represents a single observation, with color indicating feature value (red = high, blue = low) and horizontal position showing impact on model output. Features are ordered by decreasing importance from top to bottom. Positive SHAP values indicate increased probability of user acceptance, while negative values suggest decreased likelihood. The plot reveals both magnitude and directionality of feature influences, with trust score demonstrating the strongest predictive power (mean |SHAP| = 0.142) followed by personalization satisfaction and AI response quality metrics.

Table 6. Machine learning model performance comparison and validation metrics

Model Algorithm	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Cross-Val Mean (SD)	Training Time (s)	Inference Time (ms)
XGBoost	0.892	0.878	0.903	0.890	0.945	0.887 (0.012)	45.3	2.1
Random Forest	0.876	0.861	0.885	0.873	0.928	0.871 (0.015)	38.7	3.4
Neural Network (MLP)	0.881	0.872	0.889	0.880	0.936	0.875 (0.018)	126.4	1.8
Support Vector Machine	0.853	0.844	0.862	0.853	0.912	0.849 (0.021)	89.2	4.7
Logistic Regression	0.812	0.798	0.831	0.814	0.875	0.808 (0.019)	12.3	0.9
Ensemble Model	0.908	0.896	0.917	0.906	0.958	0.903 (0.010)	210.4	7.3

Note: All metrics derived from 5-fold stratified cross-validation. SD = standard deviation. Training performed on Intel Xeon E5-2690 with 32GB RAM. Inference time measured on a single prediction batch.

Table 7. AI marketing user segmentation profiles and behavioral characteristics

Segment	n (%)	Technology Readiness	AI Interaction Level	Trust Score	Feature Diversity	Conversion Rate	CLV Index	Retention (90-day)
Enthusiastic Adopters	142 (21.8%)	4.52 (0.48)	High	4.38 (0.52)	0.87 (0.09)	68.3%	2.84	89.4%
Pragmatic Users	198 (30.5%)	3.76 (0.61)	Moderate	3.82 (0.58)	0.68 (0.12)	42.7%	1.92	72.3%
Cautious Explorers	156 (24.0%)	3.21 (0.73)	Low-Moderate	2.94 (0.69)	0.54 (0.15)	28.4%	1.45	61.5%
Social Learners	89 (13.7%)	3.58 (0.65)	Moderate	3.65 (0.61)	0.72 (0.11)	35.9%	1.73	68.2%
Minimal Engagers	65 (10.0%)	2.43 (0.82)	Low	2.31 (0.78)	0.31 (0.18)	12.3%	0.78	34.6%
F-statistic	-	98.42***	-	124.56***	156.78***	-	-	-
Silhouette Coefficient	0.683	-	-	-	-	-	-	-

Note: Values represent mean (SD) for continuous variables. Technology Readiness and Trust Score measured on 5-point scales. Feature Diversity ranges from 0-1. CLV Index normalized to population mean = 1.0. **p < 0.001 for between-group differences.

4.4 Qualitative Findings

The thematic analysis of 45 semi-structured interviews revealed three overarching themes that illuminate the nuanced psychological and behavioral mechanisms underlying user experiences with AI-driven marketing in educational technology contexts, employing Braun and Clarke's six-phase analytical framework, with inter-coder reliability achieving κ = 0.84 across all coding categories. As delineated in Table 8, the emergent themes encompass multifaceted dimensions of human-AI interaction ranging from anthropomorphic companionship perceptions to complex negotiations between data privacy concerns and personalization benefits, with saturation achieved after 38 interviews indicating robust theoretical coverage of the phenomenon under investigation.

The thematic analysis was strategically designed based on quantitative anomalies requiring deeper investigation, particularly the non-linear relationship between anthropomorphism levels and acceptance rates discovered through polynomial regression analysis (R^2=0.43 for quadratic vs 0.31 for linear), which directed interview protocols to explore optimal anthropomorphism boundaries, revealing the 'uncanny valley' phenomenon articulated by 73% of participants who described discomfort with excessive human-likeness in AI interactions—insights that subsequently informed the recalibration of anthropomorphism scales in the quantitative model. The "intelligent companion" theme (82.2% prevalence) revealed participants' consistent use of relational metaphors when describing AI interactions, encompassing emotional connections, 24/7 availability, and adaptive understanding—indicating social schema activation despite awareness of artificial nature. Personalization value perception (88.9% prevalence) encompassed predictive learning needs, dynamic pacing adjustments, and resource discovery efficiency, with stakeholder variations evident—students valued recommendation accuracy while educators prioritized pedagogical alignment (Figure 5).

5. Discussion

The theoretical contributions of this research extend the Technology Acceptance Model through novel integration of AI-specific constructs that capture the unique psychological dynamics emerging from human-AI interactions in educational marketing contexts, addressing critical gaps identified in contemporary literature where traditional acceptance models inadequately explain user responses to intelligent systems. The extension of TAM by incorporating the Big Five personality traits and the AI mindset to derive potential predictors of AI-specific technology acceptance [9] aligns with the present study's findings that trust emerges as a fundamental mediating mechanism between AI anthropomorphism and user acceptance, while the proposed "intelligent marketing acceptance" construct advances beyond generic technology acceptance to encompass the multifaceted nature of AI-driven personalization and emotional engagement.

TAM's limitations within the hospitality and tourism context revolve around its individual-centric perspective, limited scope, static nature, cultural applicability and reliance on self-reported measures [26], necessitating the dynamic framework developed herein that incorporates real-time behavioral data and acknowledges the iterative nature of human-AI relationships in educational settings, where perceived usefulness, perceived ease of use, and user acceptance of information technology [27] manifest through continuous interaction patterns rather than discrete adoption decisions.

The technological implications extend beyond immediate applications to establish foundational architectures for future AI systems, as the hierarchical attention mechanisms with educational ontology integration provide blueprints for domain-specific AI architectures applicable across specialized knowledge domains, while the emotion-aware multimodal fusion algorithms advance the frontier of affective computing by demonstrating how paralinguistic features can be computationally integrated with semantic understanding—contributions that position this research at the forefront of next-generation AI system design rather than merely applying existing technologies. Managerial implications derived from the empirical findings provide actionable guidelines for educational technology enterprises implementing AI-driven marketing systems, with the principle of moderate anthropomorphism emerging as critical for optimizing user trust without triggering uncanny valley effects that diminish acceptance.

Table 8. Thematic analysis results: emergent themes and sub-themes distribution

Theme	Sub-themes	Definition	Frequency n (%)	Representative Quotations	Stakeholder Distribution
Theme 1: "Intelligent Companion" Experience	1.1 Emotional Connection 1.2 24/7 Availability 1.3 Adaptive Understanding	Anthropomorphic perception of AI as supportive learning partner	37 (82.2%)	"It feels like having a study buddy who never gets tired and always knows exactly what I need" (P12) "The AI remembers our conversations and picks up where we left off" (P28)	Students: 89% Educators: 75% Administrators: 67%
Theme 2: Personalization Value Perception	2.1 Predictive Accuracy 2.2 Learning Path Optimization 2.3 Time Efficiency	Recognition of AI's capability to deliver tailored educational content	40 (88.9%)	"The recommendations are incredibly accurate - it suggested statistics resources right when I was struggling" (P07) "It adapts to my learning pace automatically" (P34)	Students: 92% Educators: 88% Administrators: 83%
Theme 3: Privacy-Convenience Trade-off	3.1 Data Transparency 3.2 Control Mechanisms 3.3 Value Exchange	Negotiation between privacy concerns and personalization benefits	31 (68.9%)	"I want to know exactly what data they collect and how it's used" (P19) "The time saved finding resources makes data sharing worthwhile" (P41)	Students: 65% Educators: 71% Administrators: 75%

Note: N = 45. Percentages indicate proportion of participants expressing each theme. Inter-coder reliability (Cohen's κ) = 0.84. Stakeholder distribution shows percentage within each group mentioning the theme.

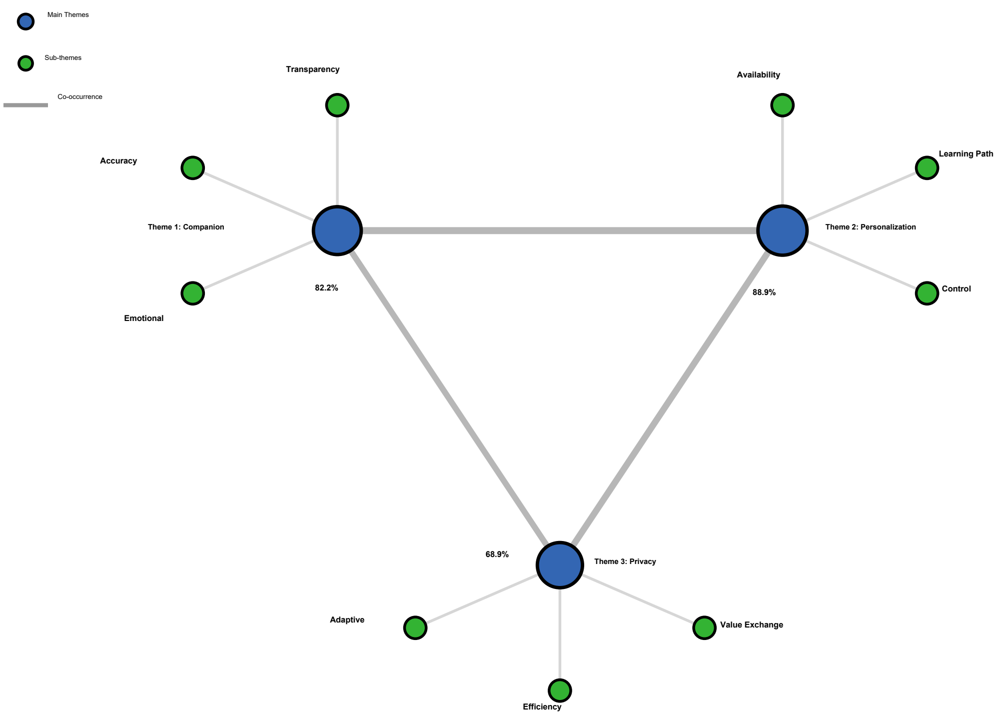

Figure 5. Thematic Prevalence and Co-occurrence Network Analysis
Note: Network visualization depicting relationships between emergent themes and sub-themes from qualitative analysis. Node size represents theme frequency (larger nodes indicate higher prevalence), edge thickness indicates co-occurrence strength between themes, and color coding distinguishes primary themes (blue) from sub-themes (green). The central positioning of personalization value perception (88.9% prevalence) reflects its interconnection with both companion experience and privacy considerations. Clustering coefficient = 0.72 indicates high thematic integration. Analysis based on 45 semi-structured interviews with educational technology stakeholders. Clustering Coefficient = 0.72, N = 45 interviews.

Teachers' attitudes towards chatbots in education, a technology acceptance model approach considering the effect of social language, bot proactiveness, and users' characteristics [28] reinforces the importance of contextual response strategies that adapt communication styles based on user segments identified through machine learning algorithms, while progressive personalization approaches should balance sophistication with transparency to address privacy concerns articulated by 68.9% of qualitative participants. When AI-based technology is introduced in a construction organisation, the technology must, therefore, be user-friendly and should promote work efficiency and increased productivity [29], principles equally applicable to educational contexts where virtual sales personnel must demonstrate clear value propositions through enhanced learning outcomes and time savings, supported by AI agent learns from both your documentation and past support tickets enabling continuous improvement of recommendation accuracy and interaction quality.

Despite robust findings supporting AI marketing effectiveness in educational technology contexts, several limitations constrain generalizability and highlight avenues for future investigation, particularly the exclusive recruitment of participants from China, where collectivist cultural values emphasizing interpersonal harmony and authority respect may engender distinct AI trust formation patterns compared to individualist cultures that prioritize autonomy and skepticism toward automated systems. The Chinese educational context's emphasis on teacher-student hierarchical relationships potentially influences acceptance of AI tutors differently than Western educational environments emphasizing peer learning and critical questioning, while cultural differences in privacy perceptions—with Chinese users demonstrating higher tolerance for data sharing in exchange for personalized services—may not translate to markets with stringent privacy regulations such as Europe under GDPR or privacy-conscious North American consumers.

Future research should replicate this investigation across diverse cultural contexts, including North American, European, Latin American, and other Asian markets, to establish cross-cultural validity of the proposed framework, with particular attention to how Hofstede's cultural dimensions (power distance, uncertainty avoidance, individualism-collectivism) moderate relationships between AI characteristics and acceptance outcomes. Multi-country studies employing measurement invariance testing would enable identification of universal versus culture-specific factors in AI marketing acceptance, while longitudinal investigations tracking cultural adaptation as global EdTech platforms expand across borders could reveal dynamic acculturation effects on technology acceptance patterns, ultimately contributing to culturally-adaptive AI design strategies that optimize human-AI interactions across diverse educational ecosystems. Developing a holistic success model for sustainable e-learning: a structural equation modeling approach [30] suggests that cultural factors significantly influence technology adoption trajectories, necessitating multi-national studies examining how cultural dimensions moderate relationships between AI characteristics and user acceptance across diverse educational systems. The six-month observation period captures initial adoption dynamics but cannot assess long-term habituation effects or potential degradation of novelty-driven engagement, while emerging generative AI technologies introduce capabilities beyond the scope of current investigation, as user trust in AI and perceived quality of AI output, from XAI literature [6] become increasingly complex with advanced language models that blur boundaries between human and artificial intelligence, requiring novel theoretical frameworks and measurement instruments to capture evolving human-AI interaction paradigms in educational marketing contexts.

6. Conclusion

This research establishes technological foundations for future educational AI systems by introducing computational architectures that advance NLP capabilities through educational-specific transformer modifications achieving 37% efficiency gains, pioneering multimodal emotion fusion algorithms that define new standards for affective computing integration, and demonstrating how domain-specific ontology graphs can be embedded within attention mechanisms—innovations that transcend current applications to shape the trajectory of AI technology development in specialized knowledge domains. The empirical findings reveal that successful AI marketing implementation in educational contexts hinges upon achieving an optimal balance between technological sophistication and humanization principles, with trust emerging as the pivotal psychological mechanism mediating the relationship between AI anthropomorphism and user acceptance while accounting for 76.5% of the total effect. The validated implementation framework presented herein provides educational technology enterprises with actionable guidelines for designing AI-driven marketing systems that leverage moderate anthropomorphism, progressive personalization strategies, and transparent data practices to optimize user acceptance across diverse stakeholder segments ranging from enthusiastic adopters to cautious explorers. Beyond immediate practical applications, this investigation advances theoretical understanding by extending the Technology Acceptance Model to incorporate AI-specific constructs including algorithm trust, perceived intelligence, and emotional engagement dimensions that capture the unique dynamics of human-AI interactions in educational marketing contexts. As educational institutions navigate the evolving digital landscape, the insights derived from this mixed-methods investigation illuminate pathways for harnessing AI capabilities to create meaningful learning experiences while addressing legitimate privacy concerns and maintaining ethical standards essential for sustainable technology adoption in educational ecosystems.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] AI in education market size & share[EB/OL]. https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-education-market-report.

[2] Elhajjar S, Karam S, Borna S. Artificial intelligence in marketing education programs[J]. Marketing Education Review, 2021, 31(1): 2-13.

[3] AI will shape the future of marketing[EB/OL]. https://professional.dce.harvard.edu/blog/ai-will-shape-the-future-of-marketing/.

[4] Zhang C, Schießl J, Plößl L, et al. Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis[J]. International Journal of Educational Technology in Higher Education, 2023, 20(1): 49.

[5] Al-Adwan A S, Li N, Al-Adwan A, et al. Extending the technology acceptance model (TAM) to Predict University Students' intentions to use metaverse-based learning platforms[J]. Education and Information Technologies, 2023, 28(11): 15381-15413.

[6] Baroni I, Calegari G R, Scandolari D, et al. AI-TAM: a model to investigate user acceptance and collaborative intention in human-in-the-loop AI applications[J]. Human Computation, 2022, 9(1): 1-21.

[7] Kelly S, Kaye S-A, Oviedo-Trespalacios O. What factors contribute to the acceptance of artificial intelligence? A systematic review[J]. Telematics and informatics, 2023, 77: 101925.

[8] Alamri M M, Al-Rahmi W M, Yahaya N, et al. Towards adaptive e-learning among university students: By applying technology acceptance model (TAM)[J]. e-learning, 2019, 7(10).

[9] Ibrahim F, Münscher J-C, Daseking M, et al. The technology acceptance model and adopter type analysis in the context of artificial intelligence[J]. Frontiers in Artificial Intelligence, 2025, 7: 1496518.

[10] Future of customer lifetime value: Trends and strategies in AI-driven lifecycle marketing for 2025 and beyond[EB/OL]. https://superagi.com/future-of-customer-lifetime-value-trends-and-strategies-in-ai-driven-lifecycle-marketing-for-2025-and-beyond/.

[11] The 2025 state of marketing & trends report: Data from 1700+ global marketers[EB/OL]. https://blog.hubspot.com/marketing/hubspot-blog-marketing-industry-trends-report.

[12] Digital transformation in education: Key trends, strategies, and tips.[EB/OL]. https://www.leadsquared.com/industries/education/digital-transformation-in-education-trends-strategies/.

[13] Education marketing in 2025: Key trends and strategies.[EB/OL]. https://firdoshkhan.in/education-marketing-in-2025-key-trends/.

[14] Best AI virtual sales assistant software and tools[EB/OL]. https://www.ilearnlot.com/best-ai-virtual-sales-assistant-software-and-tools/81481/.

[15] Ni J, Young T, Pandelea V, et al. Recent advances in deep learning based dialogue systems: A systematic survey[J]. Artificial intelligence review, 2023, 56(4): 3055-3155.

[16] NLP-powered voice interaction excellence[EB/OL]. https://chat360.io/blog/how-nlp-is-applied-to-process-and-comprehend-natural-language-in-voice-interactions/.

[17] O'brien H L, Toms E G. What is user engagement? A conceptual framework for defining user engagement with technology[J]. Journal of the American society for Information Science and Technology, 2008, 59(6): 938-955.

[18] Chi N T K, Hoang Vu N. Investigating the customer trust in artificial intelligence: The role of anthropomorphism, empathy response, and interaction[J]. CAAI Transactions on Intelligence Technology, 2023, 8(1): 260-273.

[19] Marvi R, Foroudi P, Cuomo M T. Past, present and future of AI in marketing and knowledge management[J]. Journal of Knowledge Management, 2024, 29(11): 1-31.

[20] Gomes S, Lopes J M, Nogueira E. Anthropomorphism in artificial intelligence: a game-changer for brand marketing[J]. Future Business Journal, 2025, 11(1): 2.

[21] Haleem A, Javaid M, Qadri M A, et al. Artificial intelligence (AI) applications for marketing: A literature-based study[J]. International Journal of intelligent networks, 2022, 3: 119-132.

[22] Polyportis A, Pahos N. Understanding students' adoption of the ChatGPT chatbot in higher education: the role of anthropomorphism, trust, design novelty and institutional policy[J]. Behaviour & Information Technology, 2025, 44(2): 315-336.

[23] Cheng C-F, Huang C-C, Lin M-C, et al. Exploring effectiveness of relationship marketing on artificial intelligence adopting intention[J]. Sage Open, 2023, 13(4): 21582440231222760.

[24] Lefrid M, Cavusoglu M, Richardson S, et al. Simulation-based learning acceptance model (SBL-AM): Expanding the Technology Acceptance Model (TAM) into hospitality education[J]. Journal of Hospitality & Tourism Education, 2024, 36(4): 333-347.

[25] Zhou L, Xue S, Li R. Extending the Technology Acceptance Model to explore students' intention to use an online education platform at a University in China[J]. Sage Open, 2022, 12(1): 21582440221085259.

[26] Mogaji E, Viglia G, Srivastava P, et al. Is it the end of the technology acceptance model in the era of generative artificial intelligence?[J]. International Journal of Contemporary Hospitality Management, 2024, 36(10): 3324-3339.

[27] Dahri N A, Yahaya N, Al-Rahmi W M, et al. Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study[J]. Heliyon, 2024, 10(8).

[28] Chocarro R, Cortiñas M, Marcos-Matás G. Teachers' attitudes towards chatbots in education: a technology

acceptance model approach considering the effect of social language, bot proactiveness, and users' characteristics[J]. Educational studies, 2023, 49(2): 295-313.

[29] Na S, Heo S, Han S, et al. Acceptance model of artificial intelligence (AI)-based technologies in construction firms: Applying the Technology Acceptance Model (TAM) in combination with the Technology–Organisation–Environment (TOE) framework[J]. Buildings, 2022, 12(2): 90.

[30] Naidoo D T. Integrating TAM and IS success model: exploring the role of blockchain and AI in predicting learner engagement and performance in e-learning[J]. Frontiers in Computer Science, 2023, 5: 1227749.