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THE INFLUENCE OF E-WOM ON THE USERS' PURCHASE DECISION OF M-LEARNING APPS

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ABSTRACT: This study examines the influence of electronic word-of-mouth (e-WOM) on information adoption and purchase intentions in mobile learning (M-learning) applications. By extending the Information Adoption Model (IAM) to an educational technology context, it contributes theoretically to understanding how digital peer communication shapes technology uptake. A survey of 345 Iranian young adults reveals that e-WOM significantly affects adoption decisions, with perceived usefulness emerging as a central driver of purchase intentions. The findings underscore the dual role of positive and negative user reviews in shaping app reputation and credibility. Beyond its contextual focus on Iran, where app usage is restricted, the study advances research on e-WOM dynamics in digital learning ecosystems of developing countries. The results provide practical insights for marketers, developers, and educational institutions seeking to leverage user-generated content to enhance trust, strengthen credibility, and foster wider acceptance of M-learning solutions.

Keywords: E-WOM; Purchase Intention; M-Learning Apps; Information Adoption Model

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INTRODUCTION

Rapid technological developments and the COVID-19 pandemic made mobile learning (M-learning) applications indispensable even after students across all levels returned to traditional classrooms. Mobile learning refers to a type of learning whose learner is determined previously, is not in a specific location, or benefits from the opportunities offered by mobile technologies (O'Malley et al., 2003). Statista (2024) estimates that the size of mobile e-learning will be a $48.5 billion industry by 2026, estimating an almost 150% increase since the pandemic. Alongside this estimated growth is the positive progression of online e-learning (65.84%), learning management systems (LMS) (100%), rapid e-learning (125%), and virtual classroom (191.30%) in the next two years. Therefore, understanding the key factors affecting users' acceptance and purchase intention of the M-Learning apps is vital for app developers, marketers, and mobile application stores.

M-learning is widely used in education (Miedany, 2018) and professional training (Korucu & Alkan, 2011), yet its adoption drivers in non-Western markets like Iran remain understudied. The current study seeks to find out the key predictors of M-learning adoption among Iranian users, which is a critical gap given Iran's unique socio-technological context. Without localized insights, developers and marketers risk relying on Western-centric models that may misalign with Iranian user behavior. Once the factors are known, strategies for app design, marketing, and monetization, helping bridge the digital divide and optimize resource allocation will be more precise in an underrepresented but growing market.

Thus, in studying the acceptance of M-learning apps, the researchers find the Information Adoption Model (Sussman & Siegal, 2003) apt as the study is interested in determining the significant predictors affecting adoption. Kaushal et al. (2022) concluded that e-WOM fosters trust and adoption of M-learning apps among users, and the topic is even more important, especially since not all apps can be downloaded for free, users pay particular attention to what others have to say before spending their money (Oh et al., 2015).

In this survey, we focus on the influence of the argument quality of users' comments in online communities and the source credibility of information. The study aims to explain the influence of the argument quality and source credibility of e-WOM in the online communities on the M-learning apps' perceived usefulness (PU); the influence of M-learning apps' perceived usefulness on the users' adoption of new M-learning apps, and the influence of the users' adoption of information toward M-learning apps on the purchase intention.

Comprehensive and increased knowledge of the influence of e-WOM on users' decision-making process may guide app developers, marketers, and businesses that work in the field of education, particularly in highlighting widgets and organizing content in the virtual store. Furthermore, studying e-WOM or users' comments and their roles in shaping other users' understanding of the products will inform allied disciplines such as user experience (UX) design, marketing, and mobile app development.

LITERATURE REVIEW

M-Learning Apps

With the increasing advancement in technology, screens have become smaller, and mobile device prices have become more affordable for anyone to purchase (Caudill, 2007). Earlier forms of major technologies involved in mobile learning were portable digital assistants (PDAs), Short Message Service (SMS) messaging via mobile phones, and podcasts via MP3 players (Caudill, 2007). M-learning leverages smartphones to deliver accessible, learner-centric education anytime and anywhere (E-learning Center, 2019). Indeed, the learner or the user has become the center of mobile learning. Therefore, it is essential to have the learner work with the mobile device and install mobile applications (Todoranova & Penchev, 2019).

The use of mobile apps is popular among Iranians across all generations, with Android dominating the market share at 57% (Statista, 2024). Specifically, according to StatCounter Global Stats (2023), Android dominates the mobile operating system market in Iran, accounting for 92.3%, while iOS (Apple) holds only 7.3%, primarily due to the ban on Apple products that began in May 2022. This has led to various challenges and concerns when using M-learning apps in the country. Sharples (2006) identifies several technical problems, including managing technology with short battery life and interacting with a mobile device while walking, as well as educational problems such as delivering teaching content through a small device or coordinating small-group learning in the classroom. There have been efforts to address the latter issue by developing ready-made interactive class activities accessible through M-learning apps (Bangero, 2023). Nevertheless, there remain more advantages to using the technology: easier access to learning materials; synthesized learning materials; provision of learning materials in a more accessible way – with many examples, illustrations, effects; not needing to print resources; significantly reduced time and effort required to search the needed information; facilitated communication between learners and educators; and significantly improved awareness of learners (Todoranova & Penchev, 2019).

Nevertheless, not all M-learning apps are valued equally by users and learners. In fact, according to Hussain et al. (2018), the top four dimensions for evaluating M-learning apps are effectiveness, efficiency, learnability, and user satisfaction. However, the study only focused on children. Thus, it is the researchers' interest to investigate the case of young people (aged 19 to 39), who are identified as primary users of M-learning apps in their education, career, and lifelong learning.

Electronic Word-of-Mouth

Electronic word-of-mouth (e-WOM) refers to any favorable or unfavorable remarks about a company or product by potential, current, or former customers that are shared online with a large audience (Hennig-Thurau et al., 2004). In the context of M-learning apps, these often take the form of comments, where customers publish about their experience using the products, services, and, generally, brand experience (Filieri, 2015).

As almost everything has now worked on an online presence, businesses have begun acknowledging the power of social media communication in shaping customers' attitudes (Sotiriadis & Van Zyl, 2013). Yang (2017) found support in the idea that whether a customer has a positive or negative attitude towards a product or service impacts future purchase intentions because attitudes set product expectations and can be used to compare actual performance. Lecinski (2011) explains the persuasion process, coining the Zero Moment of Truth (ZMOT). ZMOT information provided by reviews and ratings influences consumers at multiple stages in the buying process and emphasizes that consumers today may be influenced by several moments online before making a purchase decision (Lecinski, 2011; Tuten, 2023).

E-WOM facilitates consumers' information gathering (Bickart & Schindler, 2001; Chan & Ngai, 2011) and serves as a critical antecedent influencing online purchase intention and attitude (Bilal et al., 2021; Rahaman et al., 2022; Sardar et al., 2021). Extending this to technological products, empirical studies confirm that e-WOM (e.g., app reviews) significantly impacts brand success by shaping perceived credibility and usefulness (Bhandari & Pan, 2022; Talwar et al., 2021) - a dynamic particularly relevant to m-learning apps, where adoption hinges on users' trust in information quality (Liao et al., 2022).

The Information Adoption Model (IAM) (Sussman & Siegal, 2003) provides the most appropriate theoretical framework for the current study due to its focus on information-centric adoption processes. Unlike broader technology acceptance models (e.g., TAM, UTAUT) that emphasize system-related factors, IAM specifically addresses how e-WOM influences user decisions through two core mechanisms: (1) argument quality and (2) source credibility. This theoretical alignment makes IAM particularly suited for examining how e-WOM facilitates the persuasion process that ultimately leads to m-learning app purchase intentions.

Information Adoption Model

The Information Adoption Model (IAM), introduced by Sussman and Siegal (2003) integrates key elements from the Technology Acceptance Model (Davis, 1989) and dual-process models of informational influence like the Elaboration Likelihood Model (ELM) (Petty & Cacciopo, 1986). This synthesis provides a robust framework for understanding how individuals evaluate and adopt persuasive information, particularly in digital contexts. IAM has been widely applied across information systems and marketing research (Cheung, 2014; Salehi-Esfahani et al., 2016;

Song et al., 2021) due to its focus on three core determinants of information adoption: (1) perceived usefulness, (2) argument quality, and (3) source credibility.

Building upon foundational theories including the Theory of Reasoned Action (Ajzen & Fishbein, 1975), TAM, and ELM, IAM uniquely emphasizes the mediating role of usefulness assessment in information adoption processes. Perceived usefulness (PU) is defined by Davis (1989) as the "degree to which a person believes that using a particular system would enhance his or her job performance" (p.320). In the current study's context, this will refer to the use of m-learning apps to improve their learning opportunities beyond the traditional classroom experience. The other vital aspect of the model is argument quality which is referred to by Petty, Caccioppo and Goldman (1981) as the individual's subjective perception of arguments in the persuasive message - determining whether it is strong, rational, and of quality. Connecting this to the study, this refers to potential online customers' assessment of the comments or reviews read on the app stores as they decide to purchase and/or download a certain m-learning app. Finally, the third essential component is source credibility, which Bhattacherjee and Sanford (2006) defines as the extent to which the information (e.g., message, opinion, view, review) source expressed online are deemed by the recipients of the information as credible, trustworthy, believable and competent. Several studies have established how the credibility of an online source helps customers establish trust (Alsheikh et al., 2021; Anastasiei et al., 2021), more so, that argument quality has a positive impact on the perceived information utility (Alsheikh et al., 2021; Tien et al., 2019).

In essence, IAM posits that the intention to adopt a behavior or technology is heavily influenced by perceived usefulness or associated consequences (Sussman & Siegal, 2003). This theoretical approach suggests that individuals form intentions to adopt specific ideas or behaviors based on their perceived usefulness. Perceived usefulness plays a significant role in shaping adoption intentions (Wang, 2016). Empirical studies demonstrate that the perceived usefulness of information is a pivotal factor in determining whether individuals will implement it, with substantial evidence linking perceived usefulness to elevated user adoption rates and ongoing system engagement (Ismail, 2016). Another study conducted in India reveals that the adoption of mobile apps extends to increased usage and a growing intention to switch from computers and laptops to mobile apps (Roy, 2017). On the other hand, Cheung and Vogel (2012) found in their study that the ability to share information in a collaborative learning environment (in the current study's context, the virtual app stores), influences intention and behavior toward the platform.

Moreover, the determinants of perceived usefulness include the argument quality and the source credibility (Sussman & Siegal, 2003). Research indicates that argument quality—how well-reasoned and convincing the information is (Oliveira & Martins, 2011) along with the information's source credibility, referred to as the perceived trustworthiness and expertise of the information source, influences the extent to which the information is adopted (Reichelt, 2013). ELM supports this by suggesting that when individuals are motivated and able to engage deeply with the content, the argument quality becomes more important (Aghakhani et al., 2023). Conversely, in cases where individuals are less engaged, the attractiveness, likability, and credibility of the source can sway opinions. Earlier studies on source credibility have shown that messages from high-credibility sources are more likely to lead to opinion changes than those from less credible sources (Petty et al*.,* 2002). This underscores the importance of source credibility in shaping how information is processed and adopted. Asadi Damavandi and Ha's (2024) study also reveals that argument quality, which demonstrates the strength of reasoning and supporting evidence in a message, is a more effective factor in the acceptance of a technological device. This is because customers believe that strong arguments provide logical coherence and relevant evidence, making the information more persuasive (Asadi Damavandi and Ha, 2024). The findings indicate that consumer perceptions of usefulness and risk significantly impact their behavioral intentions regarding the adoption of mobile shopping apps (Vo & Wu, 2022). While information quality reduces perceived risk, source credibility and information quality positively influence perceived usefulness.nThe following hypotheses are also forwarded:

H1: Argument quality positively predicts the perceived usefulness of paid M-learning apps.
H2: Source credibility positively predicts the perceived usefulness of paid M-learning apps.
H3: Perceived usefulness of paid M-learning apps positively predicts information adoption.

H4: Information adoption positively predicts customers' purchase intention of paid M-learning apps.

RESEARCH METHOD

Data Collection

A survey involving Iranian youths was conducted. Iran was purposely selected because its mobile app market is one of the three largest markets (PocketGamer, 2019) in the Middle East, with the population skewed to young adults. About 45% of the population is 18 to 40 years old (Kemp, 2023). As there is a shortage of studies involving M-learning apps in the online market, a survey questionnaire, consisting of primarily close-ended questions and established scales validated by experts.

This study employed a snowball sampling method to collect responses from Iranian youth who had experience using paid mobile learning (M-learning) applications. To initiate the data collection process, a survey link was distributed via email to a purposive sample of 60 professional contacts known to the first author. These individuals worked in diverse industries such as education, technology, and telecommunications and were selected for their broad personal and professional networks. Each contact was asked to share the survey with young adults aged 19 to 39 who had used or were using paid M-learning apps. This approach allowed the researchers to reach a relatively diverse and distributed sample across different demographics and occupational backgrounds, although the inherent limitations of non-probability sampling are acknowledged. Finally, the total number of valid sample mobile app users was 345, see Table 1.

Table 1. Demographic Characteristics of Respondents

Dimension	Item	Frequency	Percentage
Gender	Female	168	48.70
	Male	177	51.30
Age	19-25	140	40.58
	26-32	117	33.91
	33-39	88	25.51
Education	Never attended university	45	13.04
	Undergraduate	122	35.36
	Graduate	178	51.59
Time of using m-learning apps	Less than 3 years	48	13.91
	4-6 years	59	17.10
	7-9 years	72	20.87
	10-12 years	61	17.68
	More than 12 years	144	41.74

Construct Measures

The survey instrument was structured in two sections. In the opening stage, participants were provided with a clear briefing on the objectives of the research, ensuring that their responses were grounded in an understanding of the study's purpose. This was followed by the administration of a structured questionnaire designed to capture perceptions related to the proposed model. To strengthen the rigor of the instrument, the authors consulted subject matter experts, whose evaluations enhanced its overall quality in terms of content validity, clarity, and contextual relevance. Their input ensured that the questionnaire items were not only theoretically aligned but also practically comprehensible to respondents. Following this validation step, the internal consistency of each construct was examined using Cronbach's α, a reliability coefficient widely regarded as a benchmark in behavioral research (Nunnally, 1978). As presented in Table 2, all constructs met the threshold requirements, affirming the robustness and reliability of the measurement instrument.

Table 2. Constructs and Questionnaire Measures

Item	Source	Cronbach's α
AQ1: The quality of comments is high	Sussman and Siegal, 2003	0.720
AQ2: I find the comments relevant because they fit my situation		0.720
AQ3: The comments give me clear and understandable information		0.720
AQ4: The information I received from online comments is useful		0.720
AQ5: The comments are logical	Park, Lee, and Han, 2007	0.720
AQ6: The comments provide sufficiently convincing evidence		0.720
SC1: I believe the person who posted the comments is credible	Petty et al., 2002	0.810
SC2: The credibility of the source where the comments appear is high		0.810
SC3: When the source is trustworthy, it gets my attention		0.810
PU1: M-learning apps have the potential to improve my learning	Davis, 1989	0.800
PU2: M-learning apps have the potential to improve my performance		0.800
PU3: I find using M-learning apps enjoyable		0.800
PU4: I am interested in learning how to use M-learning apps		0.800
IA1: I think discussing paid M-learning apps is useful	Sussman and Siegal, 2003	0.780
IA2: I think discussing paid M-learning apps is valuable		0.780
IA3: I think discussing paid M-learning apps is important		0.780
IA4: I think discussing paid M-learning apps is necessary		0.780
PI1: I plan on purchasing paid M-learning apps	Hsu and Lin, 2008	0.770
PI2: I plan on purchasing paid M-learning apps in the future		0.770

Data Analysis

This study analyzed the data collection by using multiple regression analysis. The reason is that the model is a relatively simple linear structure, and the aim is to test direct relationships among observed variables, rather than estimate latent constructs. Moreover, given the moderate sample size (n = 345) and the study's focus on predictive relationships rather than complex mediation or moderation effects, regression was considered both appropriate and statistically robust.

RESULTS

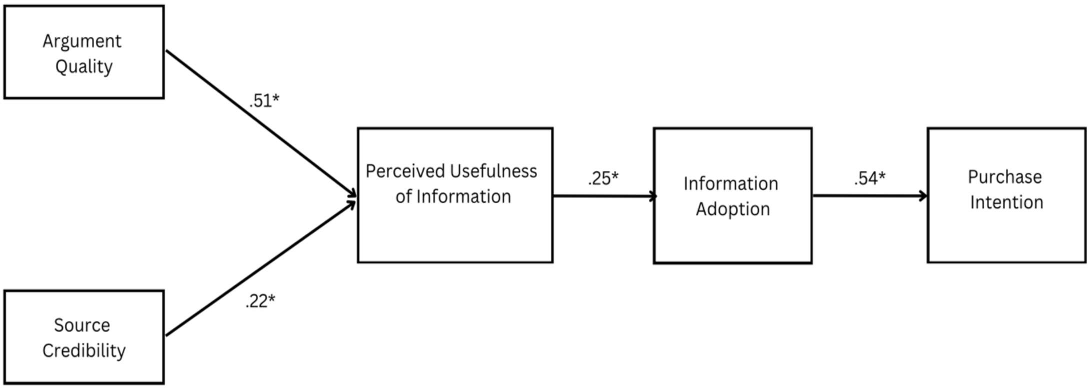
The hypotheses were tested using linear regression after verifying linearity assumptions. Results showed strong explanatory power for H1 and H2 ($R^2 = .621$, adjusted $R^2 = .412$), with both argument quality ($\beta = .51$, $p < .001$) and source credibility ($\beta = .22$, $p < .001$) significantly predicting perceived usefulness. For H3, perceived usefulness exerted a significant effect on information adoption ($\beta = .25$, $p < .001$), explaining about 40% of the variance ($R^2 = .595$, adjusted $R^2 = .401$). H4 further confirmed that information adoption strongly influenced purchase intention ($\beta = .54$, $p < .001$), accounting for roughly 50% of the variance ($R^2 = .542$, adjusted $R^2 = .502$). Taken together, the findings support all proposed hypotheses, underscoring the central role of perceived usefulness and information adoption in driving purchase intentions (see Table 4 and Figure 1).

Table 3. Regression Analysis

Hypothesis	R^2	Adjusted (R^2)	p
H_1, H_2	.621	.412	p < .001
H_3	.595	.401	p < .001
H_4	.542	.502	p < .001

Table 4. Explanatory Power of Regression Paths

Variable	B	SE	β	p
Argument Quality	.30	.03	.51	p < .001
Source Credibility	.22	.12	.22	p < .001
Perceived Usefulness	.13	.04	.25	p < .001
Information Adoption	1.01	.08	.54	p < .001



Note. * = p<.001

Figure 1. Path Analysis Toward Purchase Intention of Paid M-learning Apps

DISCUSSION

The findings of this study reinforce prior research underscoring the centrality of electronic word-of-mouth (e-WOM) in shaping consumer purchase decisions, particularly in technology-mediated educational environments. In line with Lecinski's (2011) concept of the Zero Moment of Truth and Tuten's (2023) observations on social commerce, the results confirm that user-generated feedback constitutes a decisive informational resource that shapes app reputation, user sentiment, and ultimately, purchase outcomes. Reviews—positive or negative—offer prospective users insights into app performance, functionality, and reliability, thereby guiding decisions about one-time purchases or subscription-based commitments (Hussain et al., 2018). As users form positive attitudes toward M-learning applications, strengthened by credible and detailed peer evaluations, they are not only persuaded of the apps' usefulness but are also nudged toward purchase behavior (Liao et al., 2022; Yang, 2017).

Beyond extending the Information Adoption Model (IAM) to a non-Western setting, this study makes a theoretical contribution by integrating two pivotal determinants of information adoption—argument quality and source credibility—within the broader framework of purchase decision-making. The sequential process identified begins with the evaluation of peer reviews, followed by judgments of perceived usefulness, culminating in purchase intentions. Notably, perceived usefulness emerged as a critical mediator linking e-WOM to behavioral outcomes, highlighting its role in translating cognitive evaluations into consumer action. Argument quality, defined as the logical coherence and informational richness of reviews, was the strongest predictor ($\beta = .51$, $p < .001$), consistent with the elaboration likelihood framework of Petty and Cacioppo (1986). In the context of educational technologies, where products are intangible and experiential, specific, content-rich comments—such as examples of app features, pedagogical benefits, or technical details—serve as reliable heuristics for consumers seeking to reduce cognitive load and maximize decision quality.

This interpretation resonates with behavioral economics, which emphasizes consumers' reliance on heuristics when making high-involvement or long-term decisions. Subscriptions or educational outcomes, in particular, motivate users to privilege reviews that demonstrate depth, effort, and expertise. Parallel to this, source credibility significantly shaped perceived usefulness, as users questioned not only what was said but also who articulated it. Trust was heightened when reviews originated from verifiable learners, domain experts, or long-term users, whereas suspicion was raised by anonymous or potentially biased contributions. Thus, credibility operated as a safeguard against misinformation, ensuring that perceived usefulness was anchored in dependable evaluations.

The practical implications of these findings are extensive, particularly for developers and educational platforms operating in increasingly competitive digital marketplaces. Beyond simply hosting user reviews, platforms should prioritize fostering transparency, authenticity, and systematic verification mechanisms in their feedback systems. Verified customer labels, credibility scores, or time-stamped markers such as "purchased two weeks ago" or "experienced user" can serve as trust signals that reduce skepticism and counteract fraudulent or manipulative reviews.

Similarly, mechanisms that reward users for producing detailed, content-rich evaluations—through recognition badges, loyalty points, or subscription discounts—can create incentives for quality contributions while discouraging superficial commentary. Such approaches elevate the overall quality of the informational ecosystem by ensuring that users are exposed to reviews that are both credible and substantive. This, in turn, empowers consumers to make more confident and informed purchase decisions while simultaneously generating a virtuous cycle in which trustworthy feedback spurs app refinement, improved user satisfaction, and ultimately greater customer loyalty and retention.

Marketers, meanwhile, must reconceptualize their role in light of the growing influence of consumers as active co-marketers within online environments. As Tuten (2023) emphasizes, user reviews now often carry more persuasive weight than traditional marketing and advertising efforts precisely because they are perceived as authentic, organic, and grounded in lived experience. Businesses, therefore, should adopt a proactive stance toward e-WOM by systematically encouraging feedback, actively monitoring sentiment across multiple digital touchpoints, and engaging in responsive, real-time dialogue with customers. Social listening and targeted sentiment analysis not only allow firms to neutralize potential reputational risks but also create opportunities to transform online communities into collaborative spaces of trust and advocacy. Moreover, strategic partnerships between M-learning app developers and educational institutions—particularly those involving integration with learning management systems in schools, universities, and training centers—can extend adoption and secure long-term institutional client bases. Such partnerships do not merely broaden distribution; they embed the apps within pedagogical ecosystems, creating sustained engagement and reinforcing the apps' credibility among end-users.

Finally, the study confirms that perceived usefulness is a decisive driver of purchase intention, echoing Davis's (1989) seminal Technology Acceptance Model and subsequent refinements by Hsu and Lin (2008), yet with important contextual distinctions. The contribution of this study lies in showing how e-WOM functions within emerging markets characterized by regulatory restrictions, infrastructural limitations, and heightened consumer skepticism toward digital transactions. In such environments, where opportunities for direct product trial are limited, consumers appear to substitute credible, high-quality peer feedback for first-hand experience, relying on it as a heuristic for reducing uncertainty and making informed trade-offs. For practitioners, this finding highlights the need to treat user-generated content not as a peripheral or optional marketing tool but as a strategic asset integral to product development, reputation management, and long-term market positioning. For scholars, the results extend the explanatory power of the Information Adoption Model by demonstrating how its mechanisms unfold under unique cultural and market constraints, advancing our understanding of how e-WOM operates as both a cognitive appraisal process and a behavioral catalyst in digital adoption across developing economies.

CONCLUSION

This study concludes that electronic word-of-mouth exerts a decisive influence on the adoption and purchase of M-learning applications by extending the Information Adoption Model to a non-Western context. The results highlight a sequential process in which argument quality and source credibility shape perceptions of usefulness, which in turn drive information adoption and purchase intention. Theoretical contributions lie in demonstrating the mediating role of perceived usefulness and the stronger predictive power of argument quality, while practical contributions emphasize the importance of fostering authentic, credible, and content-rich reviews to strengthen trust in digital learning marketplaces.

At the same time, several limitations should be noted. The study was limited to an Iranian sample—while valuable for exploring a large, young, and educated market, it may not fully represent other contexts. The use of snowball sampling also introduces bias, restricting the generalizability of the findings. Furthermore, the research did not account for differences across app genres (e.g., language learning vs. exam preparation) or overlaps with other categories such as entertainment and productivity, which may moderate the observed relationships. In addition, the study overlooked the role of company responsiveness to user feedback and the influence of vanity metrics such as likes or upvotes in shaping user trust. Future research should address these gaps through cross-cultural, genre-sensitive, and longitudinal designs, as well as by integrating platform-level interaction effects. For practitioners, the implications remain clear: encourage transparency, incentivize meaningful reviews, and leverage user feedback mechanisms as strategic tools to enhance adoption and sustain long-term engagement.

ETHICAL DISCLOSURE

This study adhered to ethical research standards to protect participants' rights, privacy, and confidentiality of participants. All participants provided written informed consent prior to participation after the first author secured ethics approval from the university. The participants were fully informed about the study's objectives, their voluntary participation, the right to withdraw at any time without consequences, and the confidentiality of their responses.

CONFLICT OF INTERESTS

The authors declare no conflict of interest.

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