Investigating Factors Influencing The Intention of Social Media Users to Use Generative AI for Health Misinformation Fact Checking with an Extended Technology Acceptance Model(TAM)

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Abstracts: This study expands upon Fred Davis' Technology Acceptance Model (TAM) by incorporating two external variables, perceived enjoyment and self-efficacy, to investigate the factors influencing social media users' adoption of generative AI for health misinformation fact-checking. A survey was conducted to 515 Chinese social media users, focusing on their perceptions concerning the application of generative AI in fact-checking. Notably, 79.8% of the survey participants(n=411)reported having utilized generative AI for fact-checking at least once before. Statistical analysis revealed positive correlations among perceived usefulness, perceived ease of use, perceived enjoyment, and self-efficacy in relation to users' expectations of generative AI' effectiveness in fact-checking. This study support the notion that TAM serves as a viable framework for predicting social media users' acceptance of generative AI technologies. Furthermore, the implications of this research could provide valuable insights for software developers and researchers, enhancing their comprehension of the determinants that affect user acceptance of emerging technologies. The study also offers suggestions for future research directions in this domain.

Keywords:Technology Acceptance Model; Generative AI; Health Misinformation; Fact Checking

1. Introduction

In "an era of fake news", misinformation proliferates rapidly and widely. A 2020 poll in the US indicated that 82% of Americans except to encounter misleading information on social media, with 59% of them finding it difficult to distinguish between factual and misleading information.[1] While misinformation affects various aspects of life, it is particularly problematic in the health area. Increasingly, social media users rely on online sources to learn about and investigate their health conditions, rather than visiting hospitals or healthcare centers. According to multiple studies, one-third of Facebook posts contain medically inaccurate or unverified claims[2], and 77% of YouTube videos about prostate cancer spread false information[3]. This high volume of inaccurate information online poses significant risks, impacting both quality of life and mortality rates, emphasizing the critical role of fact-checking to evaluating the credibility of incoming information.

Despite the importance of verifying outputs from generative AI tools, relying solely on human verification is impractical. A standard fact-checking process involves:(i) identifying statements for verification, (ii)formulating relevant questions, (iii)gathering evidence from pertinent sources, and(iv) determining a conclusion based on the collected evidence.[4] The immense volume and rapid generation of content make it impossible for individuals to keep pace, and the persuasive tone and appealing language of these tools further complicate the task of discerning truth. Consequently, generative AI tools may offer a more viable alternative for social media users to conduct fact-checking.

Existing studies have examines possibilities and difficulties associated with the use of generative AI in fact-checking[5]. Furthermore, some studies highlight specific challenges faced by generative AI in fact-checking, such as diminished audience trust in content that created by AI and the presence of inherent biases in AI-assisted fact-checks[6]. While numerous articles address the use of AI for misinformation correction, there remains a significant gap in research focusing on the factors influencing individuals' fact-checking behavior when using generative AI.

This study utilizes a questionnaire survey grounded in the Extended Technology Acceptance Model(TAM), which has proven to be a succinct framework that accounts for much of the variance in users' behavioral intentions regarding IT adoption and usage across a wide variety of contexts. As a new technology, generative AI encompasses both information processing and public perception. Thus, applying the TAM is suitable for investigating individuals' intentions to use generative AI in fact-checking. This study aims to explore social media users' attitude towards generative AI for fact-checking and investigate how the perceived usefulness and ease of use of generative AI and perceived enjoyment, self-efficacy influence users' willingness to perform fact checking in response to health misinformation.

2. Literature Review

2.1 Generative AI In Fact Checking

Misinformation proliferates extensively on social media, generating significant uncertainty, discord, and occasionally leading to violence surrounding critical events.

Algorithms has been increasingly employed to rapidly identify and assess claims. In contrast, platforms such as Twitter has adopted a crowdsourcing strategy, inviting users to flag potentially misleading tweets, instead of relying solely on experts to evaluate the veracity of claims[7]. Whereas predicting which assertions merit fact-checking presents a complex challenge, particularly given the vast scale of contemporary social media. However, generative AI possesses the capability to expedite this process through sophisticated algorithms, making it a viable tool for social media users who often rely on these platforms as their primary source of news.

2.2 Technology Acceptance Model (TAM)

The present study advocates for the application of the TAM to elucidate the variables significantly influencing social media users' perceptions of utilizing generative AI for fact-checking health misinformation . TAM is among the most widely employed models for investigating information technology acceptance[8]. Its theoretical foundation is rooted in the Theory of Reasoned Action (TRA) , a comprehensive social-psychological structure that has demonstrated efficacy in understanding a range of behaviors, including voting, exercise, and condom use. TAM has been specifically adapted to assess user acceptance of information systems.

Numerous empirical studies have employed TAM, and findings indicate that its explanatory power regarding attitudes towards information system usage surpasses that of TRA. King and He conducted a quantitative synthesis of TAM across multiple domains, analyzing 88 researches. Their findings indicated that TAM is a robust, highly trustworthy, and credible predictive framework applicable in diverse contexts.[9]

Within the TAM framework, perceived ease of use(PEOU) and perceived usefulness(PU) are identified as significant factors. PEOU refers to "the degree to which an individual perceives that utilizing a specific system requires minimal effort". PU is described as "the degree to which an individual believes that the utilization of a specific system would improve their job performance".[8] Davis, the originator of this theory, suggested that external variables could be integrated into TAM to enhance its predictive capabilities[8]. These external variables are posited to influence users' perceptions of PEOU and PU, which in turn affect their attitudes toward the technology. Users' attitudes subsequently shape their behavioral intentions to engage with the technology.(figure 1) Grounded in a thorough examination of the extended TAM literature, this study proposed the following research hypotheses:

H1:Perceived ease of use is positively associated with intention to use generative AI in health misinformation fact-checking

H2:Perceived usefulness is positively associated with intention to use generative AI in health misinformation fact-checking

H3:Perceived ease of use is positively associated with perceived usefulness

2.3 Perceived Enjoyment

Perceived Enjoyment (PE)represents an internal motivation that concentrates on the user experience and reflects the pleasure derived from engaging with a system.

Abdullah and Ward conducted a review of eight studies that consistently demonstrated a notable positive relationship between PE and PU.[10] From a practical perspective, Sun and Zhang illustrated this relationship through the implementation of game-based training programs and the incorporation of emoticons to enhance player enjoyment, thereby promoting the PEOU of the system.[11]

In the framework of social media users' engagement with generative AI for health misinformation fact-checking, if users perceive the experience as enjoyable, they are more likely to hold favorable views regarding both the PEOU and PU of this technology. Consequently, this enjoyment can lead to a heightened intention to utilize the technology.

Thus, I hypothesize:

H4:Perceived enjoyment is positively associated with perceived ease of use

H5:Perceived enjoyment is positively associated with perceived usefulness

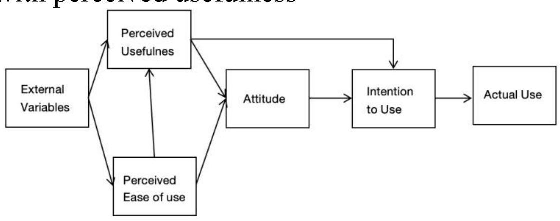

Figure 1. Original TAM

2.4 Self-Efficacy

Self-efficacy (SE) is identified as individuals' beliefs in their abilities to mobilize the necessary motivation, mental faculties, and strategies required to effectively address specific demands.According to Bandura, SE significantly influences motivation and behavior, serving as a fundamental determinant of user actions.[12]

The theory of self-efficacy has been applied across various disciplines including consumer behaviors, psychology , organizational behavior and information systems. For example, Siu-Cheung and Ming-te extended the model by integrating Subjective Norm and Bandura's Social Cognitive Theory (self-efficacy) to elucidate the intention to utilize internet banking in Hong Kong.[13]

Abdullah and Ward reviewed a review of 41 studies investigating the influence of SE on users' PEOU, finding that 33 of these studies exhibited a considerable and positive effect of SE on PEOU.[10] However, the literature presents mixed results concerning the relationship between SE and PU. While various researches have identified a significant positive relationship between SE and PU[14], others have reported no substantial association between these constructs.[15] To further explore the impact of SE on PEOU and PU, this study proposes the following research hypotheses:

H6:Self-efficacy is positively associated with perceived ease of use of generative AI

H7:Self-efficacy is positively associated with perceived usefulness

As previously discussed, this study incorporates perceived enjoyment and self-efficacy as external variables within the TAM, as shown in Figure 2.

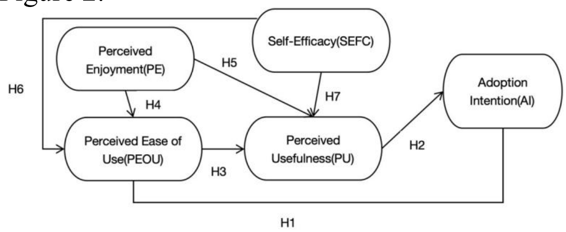

Figure 2. The structural Model of the Hypotheses

3. Methods

In this study, I tested hypotheses aimed at predicting social media users' behavioral intentions to utilize generative AI for fact-checking health misinformation. A quantitative methodology was employed as it yields reliable, valid, objective and generalizable findings, enabling the distribution of questionnaires to a broad participant pool. The research design consisted of two sections. The first section collected data on the demographic profiles and generative AI usage of the respondent. The second section consisted of 20 questions: four addressing SE, three pertaining to PE, five focusing on PEOU, five on PU, and three on intended use. The questions were adapted from prior studies, with slight modifications in wording to better align with the context of generative AI. The measures for PEOU, PU and IU of generative AI were derived from the work of Choung et al.[16]. Furthermore, the scale for measuring PE was derived from Venkatesh et al.,[17] with adjustments made to fit the generative AI context. The SE scale was developed and validated grounded in the study carried out by Kulviwat et al.[6] Respondents assessed their level of agreement using a five-point Likert scale, labeled as 'Strongly Disagree', 'Disagree', 'Neutral', 'Agree', and 'Strongly Agree', associated with scores spanning 1 to 5, respectively.

The respondents in this study were social media users in China, yielding a total of 515 completed surveys. Among these participants, 104 individuals (20.2%) reported that they had not previously utilized generative AI. Consequently, non-users were excluded from further questioning regarding generative AI. Thus, the subsequent analysis was confined to responses from 411 users who had prior experience with generative AI, ensuring that the data collected reflected direct user engagement with this technology. The sample comprised 216 male respondents (52.55%) and 195 female respondents (47.45%), reflecting a balanced gender distribution. Nearly half of the participants held an undergraduate degree (43.55%). To obtain valid results, samples were from different genders, ages, educational groups and professional positions. Furthermore, incomplete and unreasonable responses were removed.

The collected data were subjected to correlation and regression analyses utilizing the SPSS. Cronbach's Alpha test was conducted for all constructs to assess internal consistency across the items for each measure. All variables in the study reported alpha calculations(as shown in Table 1) exceeding the accepted threshold of 0.70 for social science research, indicating satisfactory reliability for all measures.

Table 1. Reliability Analysis

Variables	Number of items	Klonbach Alpha
Self-efficacy	4	0.827
Perceived enjoyment	3	0.812
Perceived ease of use	5	0.852
Perceived usefulness	5	0.892
Intended use	3	0.821

Table 2. Lateral Collinearity Assessment and Hypothesis Testing

Hypothesis	Relationship	VIF	Std Error	Std Beta	T-value	P Value	R^2
H1	PEOU→AI	1.209	0.052	0.324	7.570	<0.001	0.384
H2	PU→AI	1.209	0.043	0.411	9.611	<0.001	
H3	PEOU→PU	1.446	0.058	0.114	2.432	<0.001	0.377
H7	SE→PU	1.382	0.053	0.301	6.537	<0.001	
H5	PE→PU	1.408	0.046	0.339	7.309	<0.001	
H6	SE→PEOU	1.240	0.043	0.313	6.830	<0.001	0.308
H4	PE→PEOU	1.240	0.037	0.341	7.438	<0.001	

3. Results

Table2 delineates the results of the evaluations performed on the structural framework. First, issues of multicollinearity were addressed using the Variance Inflation Factor (VIF). For satisfactory assessment, VIF values are deemed acceptable when they exceed 0.2 and do not surpass 5.0. [18] All inner VIF values for the independent variables in this study fell within this acceptable range, indicating that multicollinearity is not a concern.

Second, the t-values for all relationships were calculated to evaluate the significance levels of the relationships within the model. As shown in Table 2, all relationships exhibited t-values exceeding 1.645, indicating statistical significance.

Table 3. Summary of Hypotheses Testing

Hypothesis	Effects	Direction	Path Coefficient	Conclusion
H1	PEOU→AI	Positive	.324	Supported
H2	PU→AI	Positive	.411	Supported
H3	PEOU→PU	Positive	.114	Supported
H4	PE→PEOU	Positive	.341	Supported
H5	PE→PU	Positive	.339	Supported
H6	SE→PEOU	Positive	.313	Supported
H7	SE→PU	Positive	.301	Supported

The findings confirm the relationships among the independent variables on the dependent variables. Specifically, the independent variables account for 30.8% (R^2=0.308), 37.7% (R^2=0.377), and 38.4% (R^2=0.384) of the variance in PEOU, PU, and AI, respectively. This data supports the relationships proposed by TAM.

Furthermore, PEOU (β=0.324, t-value=7.570, $p<0.001$) and PU (β=0.411, t-value=9.611, $p<0.001$) were found to positively influence social media users' adoption intention (AI) regarding generative AI for health misinformation fact-checking, thereby supporting Hypotheses 1 and 2. Additionally, PEOU (β=0.114, t-value=2.432, $p<0.001$), SE(β=0.301, t-value=6.537, p<0.001), and PE(β=0.339, t-value=7.309, p<0.001) positively affected PU, thus validating Hypotheses 3, 7, and 5. In terms of PEOU, both SE (β=0.313, t-value=6.830, p<0.001) and PE (β=0.341, t-value=7.438, p<0.001) demonstrated positive effects, supporting Hypotheses 6 and 4. A summary of the hypothesis testing results is provided in Table 4.positively and affects social media users' adoption intention(AI) of generative AI in health misinformation fact-checking. Hence, hypothesis 1 and hypothesis 2 are supported. Furthermore, PEOU(β=0.114, t-value=2.432, P<0.001), SE (β=0.301, t-value=6.537, p<0.001) and PE (β=0.339, t-value=7.309, p<0.001) positively affects PU. Therefore, hypothesis 3, hypothesis7 and hypothesis 5 are accepted. In terms of PEOU of generative AI, SE(β=0.313, t-value=6.830, p<0.001) and PE(β=0.341, t-value=7.438, p<0.001) positively affect PEOU. Hence, hypothesis 6 and hypothesis 4 are supported. A summary of hypotheses testing results are provided in Table 3.

4. Discussion

The primary objective of this study is to investigate the variables influencing social media users' adoption intentions (AI) in terms of the utilize of generative AI for health misinformation fact-checking.

The findings of this study demonstrate that the core variables of TAM, specifically PU and PEOU, are significantly related to AI. Collectively, PU and PEOU account for approximately 40% of the variance in social media users' intentions to utilize generative AI for fact-checking health misinformation. Consistent with Davis's findings[8], PEOU plays a critical role in influencing users' willingness to use generative AI, while PU exerts a greater influence on adoption intention than PEOU.

The support for all hypothesized relationships suggests that TAM, augmented by the external variables of perceived enjoyment and self-efficacy, serves as a suitable framework for examining social media user acceptance of generative AI.

Applying TAM to the context of generative AI in health misinformation fact-checking indicates that social media users are predisposed to use this technology due to their perception of its utility and ease of use in meeting their fact-checking needs. However, it is essential for users to exercise caution and not blindly trust the content produced by generative AI, as this technology is capable of generating large volumes of human-like text, which can be employed to create persuasive misinformation.

Perceived enjoyment exerted the strongest influence on social media users' attitudes toward the utility of generative AI in health misinformation fact-checking. This finding aligns with prior studies that established a significant relationship between PE and PU of new technologies.[19] Furthermore, self-efficacy emerged as a substantial factor contributing to users' perceptions of generative AI's usefulness. Additionally, PEOU was identified as another variable related to PU. The greater the usability of the system, the more likely users are to recognize its utility.When examining the factors that contribute to PEOU, the results revealed no notable difference between PE and SE.This suggest that when users experience greater enjoyment and feel more confident in their ability to utilize generative AI for health misinformation fact-checking, they are likely to find the system easier to navigate.

This study does, however, have several limitations. First, it was restricted to Chinese social media users, where the adoption of generative AI is relatively uncommon, potentially affecting the comprehensiveness of the findings. Second, the study did not incorporate the perceptions of non-users, thereby leaving unexplored the reasons why some individuals choose not to engage with generative AI for health misinformation fact-checking. Third, the study focused on a limited set of factors, possibly overlooking other influences, such as users' loyalty to alternative fact-checking tools.

Future research should encompass a broader population of social media users, including both those who utilize generative AI and those who do not, to better understand the motivations behind the adoption or rejection of this technology. Additionally, further investigation into other influencing factors would enhance the comprehensiveness and credibility of the research, ultimately providing generative AI developers with valuable insights to improve user experience and service offerings.

5. Conclusion

This study, utilizing an extended Technology Acceptance Model (TAM), elucidates the factors influencing social media users' perception of generative AI for fact-checking purposes. The findings indicate that higher levels of perceived enjoyment, self-efficacy, perceived usefulness, and perceived ease of use significantly contribute to users' intentions to employ generative AI for health misinformation fact-checking.

However, it is crucial that the advancement of generative AI is accompanied by a comprehensive understanding of the potential misinformation it may generate. This research is of considerable significance as it provides insights into genuine user perceptions of generative AI, enhancing the existing literature on technology adoption within the scope of health misinformation.

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