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# THE IMPACT OF DEEPFAKE TECHNOLOGY ON PUBLIC TRUST IN RETAIL SYSTEMS

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## ABSTRACT

In the context of the rapid evolution of digital marketing within the retail industry, DeepFake technology poses significant challenges to consumer trust. Aiming to investigate the impact of DeepFake on public trust in digital marketing in retail systems, this study employs a Structural Equation Modeling (SEM) approach, integrating elements from the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM). Data were collected from 346 consumers to support the analysis. The findings reveal that technological infrastructure, legal frameworks, subjective perceptions, social influence, and social trust all have a positive and statistically significant impact on public trust in digital marketing. Moreover, the study confirms that consumer trust serves as a crucial mediating factor influencing purchase intention.

**KEYWORDS**: DeepFake; Public Trust; Digital Marketing; Consumer Behavior; Retail Systems.

## 1. INTRODUCTION

Trust is a fundamental element in maintaining sustainable social relationships, fostering social cohesion, and ensuring the effective functioning of institutions. According to Võ Minh Sang (2016), trust is a broad concept referring to confidence in a subject, whereas belief is typically associated with specific manifestations or affirmations of that subject. Expanding on this perspective, Nguyễn Quý Thanh and Nguyễn Thị Khánh Hòa (2013) argue that trust reflects confidence in the characteristics, competence, and reputation of an individual or entity, while belief tends to be more intrinsic, often associated with spiritual or religious convictions. From a sociological standpoint, Trần Hữu Quang (2006) emphasizes that interpersonal trust is a complex psychological–socio–cultural phenomenon and serves as a foundational condition for collective life.

From an international lens, Giddens (1996) highlights that trust stabilizes social relationships and facilitates cooperation even in the absence of certainty, enabling social actions in conditions of risk. Castelfranchi and Falcone (1999) approach social trust from a cognitive perspective, framing it as a dynamic construct shaped by expectation, emotion, and the evaluation of intentions. In the context of digital marketing, consumer trust functions as a crucial mediating variable influencing purchase intention and brand loyalty (Gefen et al., 2003; Pavlou, 2003).

DeepFake refers to a technological application of artificial intelligence (AI) and deep learning (DL) that employs deep neural networks (DNNs), especially generative adversarial networks (GANs), to produce hyper-realistic fabricated multimedia content such as images, videos, and audio (Vasist & Krishnan, 2022). The underlying mechanism involves two neural networks: a generator, which creates synthetic content, and a discriminator, which evaluates its authenticity (Saiyad & Vivek, 2022). While the technology offers new potential in content generation, it simultaneously introduces severe risks to communication, public trust, and media credibility.

As Mika (2019) notes, DeepFake is not merely a technological tool but a formidable threat to the integrity of media and public discourse. On social media platforms, DeepFake-generated misinformation spreads rapidly, potentially distorting public perception, manipulating opinion, and impacting political and economic events. In the realm of digital marketing, DeepFake content can severely erode consumer trust in brand messaging and advertising strategies.

The term “digital marketing” emerged in the 1990s as the Internet began to play a pivotal role in communication and commerce (Damian, 2012). According to Kotler and Armstrong (2009), digital marketing refers to the use of electronic technologies to directly connect businesses and consumers through websites, social media, emails, forums, and interactive television. This form of marketing allows firms to expand reach, personalize consumer experiences, and optimize promotional expenditures.

Dave and Ellis (2018) define digital marketing as the process of achieving marketing objectives through digital media, data, and technology. Kingsnorth (2016) adds that digital marketing involves the application of conventional marketing strategies across digital platforms such as search engines, social networks, and mobile devices, allowing for real-time feedback, data-driven adjustments, and enhanced campaign efficiency.

This research draws upon two well-established models: the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to examine how DeepFake technology influences public trust in digital marketing. TPB posits that behavioral intentions are shaped by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991), while TAM emphasizes perceived usefulness and perceived ease of use as key determinants of technology acceptance (Davis, 1989). Integrating these models, the study employs Structural Equation Modeling (SEM) to analyze the effects of technological infrastructure, legal framework, subjective perception, social influence, and social trust on public trust, which in turn mediates the intention to purchase.

## 2. THEORETICAL FOUNDATION AND RESEARCH MODEL

The study adopts two well-established theoretical frameworks: the Technology Acceptance Model (TAM) developed by Fred Davis in 1986, and the Theory of Planned Behavior (TPB) proposed by Icek Ajzen in 1985. The TAM is widely used to explain how users' approach and adopt new technologies. In this model, Behavioral Intention (BI) represents a user's willingness to adopt the technology, and Actual System Use is directly influenced by BI. In parallel, the TPB is employed to predict an individual's behavioral intention, which is considered the most immediate antecedent of actual behavior (Ajzen, 1991). This intention is shaped by three key components: Attitude toward the Behavior, referring to the individual's positive or negative evaluation of performing the behavior; Subjective Norm, which reflects perceived social pressure or influence from others significant to the decision-maker; and Perceived Behavioral Control, indicating the extent to which individuals feel capable of executing the behavior in question. The integration of TAM and TPB allows for a more comprehensive understanding of both technological and psychological determinants of user behavior in technology adoption contexts

### 2.1. Technological Infrastructure

Technological infrastructure plays a critical role in shaping consumer trust toward marketing content that incorporates DeepFake technology. Individuals with greater access to modern digital devices, stable internet connectivity, and advanced digital literacy tend to exhibit higher levels of trust. This can be attributed to their more extensive understanding of technology, greater ability to discern between authentic and synthetic content, and deeper knowledge of how DeepFake systems function. According to Gefen, Karahanna, and Straub (2003), technological knowledge and access to digital infrastructure are essential components in forming knowledge-based trust in online environments. Their findings suggest that consumers who are well-versed in digital technologies are more likely to engage confidently with digital content. Similarly, McKnight, Choudhury, and Kacmar (2002) emphasize that perceived adequacy of technological infrastructure significantly influences the development of initial trust, especially in virtual contexts where face-to-face cues are absent. Therefore, this study proposes the following hypothesis:

***H1:** Technological infrastructure has a positive influence on consumer trust in marketing content generated using DeepFake technology.*

### 2.2. Legal Framework

Technological infrastructure plays a critical role in shaping consumer trust toward marketing content that incorporates DeepFake technology. Individuals with greater access to modern digital devices, stable internet connectivity, and advanced digital literacy tend to exhibit higher levels of trust. This can be attributed to their more extensive understanding of technology, greater ability to discern between authentic and synthetic content, and deeper knowledge of how DeepFake systems function.

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***H2:*** *Perceived legal safeguards related to DeepFake technology positively influence consumer trust in marketing content that utilizes DeepFake*

## 2.3. Social Influence

Social factors, including the opinions of family members, friends, social media influencers, and online reviews—play a pivotal role in shaping consumer trust in marketing content that utilizes DeepFake technology. When individuals are part of a social network that holds favorable attitudes toward the adoption of DeepFake in marketing, they are more likely to develop similar levels of trust. This phenomenon reflects the power of social norms and peer influence in forming perceptions in digitally mediated environments. Ajzen (1991) emphasized the importance of subjective norms, defined as an individual's perception of social pressure to perform or avoid a particular behavior. In the context of technology acceptance, Venkatesh, Morris, and Davis (2003) also confirmed that social influence is a critical determinant of behavioral intention, particularly during the early stages of technology diffusion when users rely on external cues for guidance. Based on these theoretical foundations, the following hypothesis is proposed:

***H3:*** *Social norms have a positive influence on consumer trust in marketing content that incorporates DeepFake technology*

## 2.4. Subjective Perception

Consumers' subjective perceptions, including perceived usefulness, transparency, entertainment value, and added benefits, significantly influence their level of trust in DeepFake-based marketing content. When consumers perceive this technology as providing tangible benefits such as personalized shopping experiences or engaging and creative content, they are more inclined to trust and accept it. Conversely, when they view DeepFake as deceptive, manipulative, or potentially invasive of privacy, their trust is likely to diminish. According to Davis (1989), perceived usefulness and perceived ease of use are key drivers of user attitudes toward technology. Building on this foundation, Gefen, Karahanna, and Straub (2003) extended the model by highlighting the close relationship between subjective perception and the development of trust, especially in high-risk contexts such as e-commerce. These findings suggest that trust is not only based on objective features but also on the user's cognitive and emotional interpretation of the technology. Thus, the following hypothesis is proposed:

***H4:*** *Subjective perception has a positive influence on consumer trust in marketing content that utilizes DeepFake technology.*

### 2.5. Social Trust

An individual's general level of trust in society, institutions, and brands can be translated into specific trust in marketing content utilizing DeepFake technology. Individuals with a high propensity to trust are typically more receptive to innovative marketing approaches, including DeepFake-based content, compared to those who are naturally skeptical or less trusting of technology. McKnight et al. (1998) developed two foundational constructs in trust research: disposition to trust and institutional trust. Their findings revealed that these components are critical in forming trust in newly established relationships, especially in technology-mediated contexts. Within the scope of DeepFake applications, social trust may serve as a trust-enabling mechanism that reduces perceived risk and enhances consumers' openness to innovation. Accordingly, the following hypothesis is proposed:

***H5:*** *Social trust has a positive influence on consumer trust in marketing content that utilizes DeepFake technology.*

### 2.6. Consumer Trust

When consumers perceive DeepFake-based marketing content as authentic, transparent, and value-enhancing, they are more likely to develop strong purchase intentions. Trust functions as a mechanism that mitigates uncertainty and perceived risk, facilitating the transition from consumer interest to actual purchasing behavior. Numerous studies have validated the positive relationship between trust and purchase intention in e-commerce contexts. For instance, Pavlou (2003) integrated trust into the Technology Acceptance Model (TAM) and found that trust was a critical antecedent of online purchase intention. Similarly, Kim, Ferrin, and Rao (2008) proposed a trust-based decision-making model in online shopping, demonstrating that trust not only directly impacts purchase intention but also indirectly reduces perceived risk. From the lens of the Theory of Planned Behavior (TPB), trust can be interpreted as an affective factor influencing attitudes toward behavior, which subsequently shapes behavioral intention, in this case, the intention to make online purchases (Ajzen, 1991). Based on this rationale, the following hypothesis is proposed:

***H6:*** *Consumer trust has a positive influence on online purchase intention.*

### 2.7. Proposed Research Model

The proposed research model is theoretically grounded in two influential frameworks: the TAM developed by Fred Davis (1986) and the TPB proposed by Icek Ajzen (1985). These models serve as the conceptual foundation for examining how DeepFake technology impacts public trust in digital marketing, particularly in the context of retail social media platforms. The model incorporates five key antecedents, technological infrastructure, legal framework, social influence, subjective perception, and social trust, which are hypothesized to influence consumer trust. In turn, consumer trust is expected to directly influence online purchase intention. A total of six hypotheses (H1 to H6) are proposed, all positing positive or direct effects on consumer trust and behavioral intention. The proposed model is illustrated in **Figure 1**.

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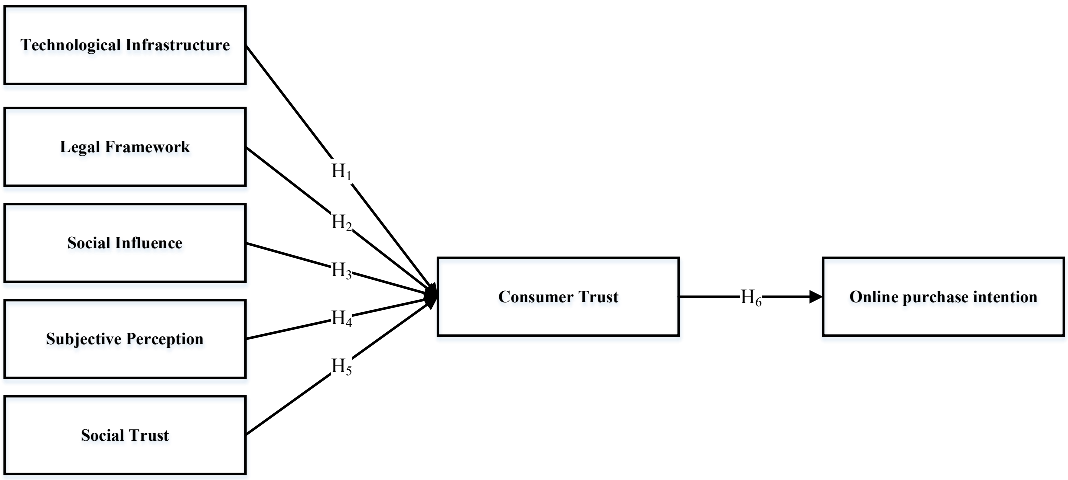


**Figure 1:** Model research

The proposed research model is developed based on theoretical foundations from the TAM and the TPB, with a specific focus on consumer trust in the context of DeepFake marketing content. As illustrated in Table 1, the model incorporates multiple key constructs and their associated observable variables (indicators), which have been carefully designed to measure both psychological and behavioral dimensions of consumer.

Each latent variable in the model represents a theoretical factor that is hypothesized to influence consumer trust or online purchase intention. These include constructs such as Technological Infrastructure, Perceived Legal Safeguards, Social Norms, Subjective Perception, Social Trust, and Consumer Trust. Each construct is operationalized through multiple indicators, which are grounded in prior validated scales and aligned with recent scholarly insights. The integration of these variables into a cohesive framework enables a systematic investigation of how environmental, social, and individual perceptions collectively shape trust in DeepFake marketing and subsequent purchase decisions.

**Table 1:** Detail of model research

| *H* | *Sign* | *Factors* | *Indicator* | *References* |
|---|---|---|---|---|
| H1 | CSHT | Technological infrastructure has a positive impact on consumer trust in DeepFake marketing content. | | |
| | 1 | CSHT1 | I have easy access to modern digital devices (e.g., smartphones, laptops) that support multimedia content. | Gefen et al., (2003) |
| | 2 | CSHT2 | I have stable and high-speed internet connectivity to view and assess online media content. | McKnight et al., (2002) |
| | 3 | CSHT3 | I possess sufficient digital literacy to evaluate the credibility of multimedia marketing content. | McKnight et al. (1998) |

| | | | | |
|---|---|---|---|---|
| | 4 | CSHT4 | I understand the basic functioning and implications of DeepFake technology. | Vasist & Krishnan (2022 |
| H2 | HLPL | Perceived legal safeguards related to DeepFake positively influence consumer trust. | | |
| | 5 | HLPL1 | I am aware of existing legal regulations regarding the use of DeepFake in marketing and media. | McKnight & Chervany (2001) |
| | 6 | HLPL2 | I believe that laws and regulations effectively protect consumers from the misuse of DeepFake content. | Pavlou (2003): |
| | 7 | HLPL3 | I think that organizations using DeepFake in marketing are legally accountable for misleading content. | Kim et al., (2008) |
| | 8 | HLPL4 | I feel more confident when there is transparency about the use of DeepFake in advertisements. | Belanche et al. (2021) |
| H3 | AHX H | Social norms have a positive impact on consumer trust in DeepFake marketing content. | | |
| | 9 | AHXH 1 | People around me (e.g., family, friends) support the use of advanced technologies like DeepFake in marketing. | Ajzen (1991) |
| | 10 | AHXH 2 | I feel encouraged to trust DeepFake-based content when it is accepted by my social circle. | Venkatesh et al. (2003): |
| | 11 | AHXH 3 | Influencers or opinion leaders I follow support or use DeepFake in marketing content. | Liu et al. (2022) |
| | 12 | AHXH 4 | Positive online reviews and user comments increase my trust in DeepFake advertisements. | Hajli et al. (2015) |
| | 13 | AHXH 5 | I would be more likely to trust DeepFake marketing if it is commonly accepted by others on social media. | Zhu et al. (2021) |
| H4 | NTCQ | Subjective perception has a positive impact on consumer trust in DeepFake marketing content. | | |
| | 14 | NTCQ 1 | I believe that DeepFake-based marketing content is creative and engaging. | Gursoy et al. (2022) |
| | 15 | NTCQ 2 | I find DeepFake marketing content to be useful in helping me evaluate products or services. | Davis (1989) |

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| | | | | |
|---|---|---|---|---|
| | 16 | NTCQ 3 | I perceive DeepFake content to be transparent and informative when used responsibly. | Belanche et al. (2021) |
| | 17 | NTCQ 4 | I believe that DeepFake content adds value to the digital customer experience. | Chatterjee et al. (2023) |
| | 18 | NTCQ 5 | I feel entertained when I watch DeepFake-enhanced advertisements. | De Cicco et al. (2021) |
| H5 | LTXH | Social trust has a positive impact on consumer trust in DeepFake marketing content. | | |
| | 19 | LTXH 1 | I believe that people in my online community generally share trustworthy marketing content. | Kim & Peterson (2021) |
| | 20 | LTXH 2 | I think that most consumers can distinguish between real and fake content in online media. | Luo et al. (2023) |
| | 21 | LTXH 3 | I trust the collective judgment of people in my social network when it comes to DeepFake content. | Mohammadi et al. (2022) |
| | 22 | LTXH 4 | I tend to believe marketing content if it is widely accepted and shared within my community. | Shin & Park (2020) |
| | 23 | LTXH 5 | I am influenced by the general trust level of my society in judging online marketing content. | Chae et al. (2023) |
| H6 | LTNT D | Consumer trust positively influences online purchase intention. | | |
| | 24 | LTNT D1 | I am more likely to purchase online if I trust the website or seller. | Pavlou (2003) |
| | 25 | LTNT D2 | My trust in online marketing content increases my willingness to make purchases. | Gefen et al. (2003) |
| | 26 | LTNT D3 | I feel confident in making online purchases when I trust the brand or platform. | Hajli et al. (2014) |
| | 27 | LTNT D4 | Trust in product information encourages me to complete online transactions. | Kim et al. (2008) |
| | 28 | LTNT D5 | The higher my trust in a retailer's online content, the more likely I am to buy from them. | McKnight et al. (2002) |

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| H7 | YDMH | Decision of online purchase intention | | |
|---|---|---|---|---|
| | 29 | YDMH 1 | I am likely to purchase a product online if the promotional video appears realistic and trustworthy. | Cheng & Jiang (2023) |
| | 30 | YDMH 2 | DeepFake-enhanced marketing content increases my interest in buying products online. | Floridi et al. (2022) |
| | 31 | YDMH 3 | When DeepFake technology is used effectively in advertising, it positively affects my purchase decision. | Sabagh et al. (2021) |

## 3. METHODOLOGY

### 3.1. Research process

The primary objective of this study is to examine the impact of DeepFake technology on consumer trust and online purchase intention within retail systems operating on social media platforms. To address this aim, the research team employed a quantitative survey method, distributing online questionnaires to consumers located in Hanoi. The survey instrument was developed based on established scales from prior research related to trust, DeepFake technology, and digital marketing. Specifically, the survey comprised 31 items, designed to reflect the core constructs from the TAM and TPB models.

Data collection yielded 346 valid responses of the total 400 distributed questionnaires. The dataset was subsequently analyzed using a combination of statistical techniques, including descriptive statistics, EFA, Cronbach's Alpha reliability testing, correlation analysis, regression analysis, and SEM. These analytical procedures were employed to evaluate the measurement validity, test the hypothesized relationships, and validate the overall structural integrity of the proposed research model.

### 3.2. Developing the Study Questionnaire

The questionnaire used in this study was systematically developed based on the proposed hypotheses and synthesized insights from prior empirical research. It comprised a total of 31 measurement items, including 28 items designed to assess the antecedent factors influencing consumer trust and behavioral responses, and 3 items specifically measuring online purchase intention.

The instrument was structured into two distinct sections. The first section evaluated respondents' perceptions and attitudes toward the constructs identified in the research model. Participants were asked to express their level of agreement with 28 statements using a 5-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. This approach allowed for the quantification of subjective attitudes and facilitated subsequent statistical modeling.

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The second section gathered demographic and contextual information, including variables such as age, gender, education level, and frequency of online shopping. This data was utilized to perform descriptive statistical analysis and to examine how individual characteristics may moderate or influence the relationship between trust-related factors and online purchase intention in the context of DeepFake-enhanced digital marketing.

## 4. RESEARCH RESULTS AND DISCUSSION

### 4.1. Descriptive statistics

The study employed a mixed-methods data collection approach, combining an online survey via Google Forms and a series of in-depth interviews with selected consumers who demonstrated awareness of DeepFake technology. A total of 346 valid responses were obtained, primarily from participants representing retail businesses (sellers). In terms of age distribution, the majority of respondents fell within the 18–22 age group (36.7%), followed by those aged 23–40 (22.3%). Notably, 21.1% of respondents were under 18, and 11.8% were between 41–55. Only 8.1% were over 55 years old, suggesting a youthful and digitally active sample.

Regarding occupational status, students accounted for the largest group (34.1%), followed by employed individuals (31.8%) and high school students (20.2%). Smaller proportions were homemakers (9.0%) and retirees (4.9%), indicating a majority of participants actively engaged in work or study. With respect to educational attainment, 37.6% held a university degree, and 25.4% had a college or vocational diploma. Meanwhile, 22.3% had completed only high school or less. Postgraduate degree holders represented 7.2%, and 7.5% reported other educational levels. In examining technological exposure, 18.8% of respondents were actively working or studying in the IT field, and 30.3% had no formal affiliation but showed interest in information technology. Another 26.6% were involved in related technological fields such as electronics and telecommunications. However, 16.5% had no connection to the tech sector, and 7.8% were undecided about their educational or professional direction. As for online shopping behavior, a substantial proportion of participants reported frequent engagement: 35.5% purchased occasionally, 25.4% had made many purchases, and 23.4% were regular online shoppers. Conversely, only 4.0% indicated they had never shopped online. In terms of awareness of DeepFake technology, 37.3% of participants had heard about DeepFake but lacked detailed knowledge, while 25.7% reported moderate familiarity. Only 11.8% claimed to have a deep understanding, and 14.7% had never heard of the term. Concerning sources of information, 25.7% encountered DeepFake through traditional media (TV, newspapers, radio), while 21.4% became aware through academic or professional contexts. Social media was a key source, cited by 19.4%, and 20.2% learned from peers. Notably, 13.3% had never heard of DeepFake from any source.

### 4.2. Cronbach's Alpha Test

To ensure the reliability of the measurement scales in the proposed model, the study employed Cronbach's Alpha reliability testing using SPSS version 20. This procedure was conducted to evaluate the internal consistency of the observed items within each construct. As shown in Table 2, the analysis

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revealed that all 31 items demonstrated Cronbach's Alpha coefficients exceeding the threshold value of 0.60, and their corrected item-total correlation coefficients were greater than 0.30. According to the guidelines by Hair et al. (2010, 2017), these thresholds indicate acceptable reliability and internal consistency for exploratory research. Therefore, all measurement items met the minimum reliability standards and were deemed suitable for inclusion in the subsequent Exploratory Factor Analysis (EFA) phase.

**Table 2:** Cronbach's Alpha coefficients

| *No.* | *Hypothesis* | *Construct* | *Code* | *Initial Items* | *Items Retained* | *Cronbach's Alpha* | *Items Removed* |
|---|---|---|---|---|---|---|---|
| 1 | H1 | Technological Infrastructure | CSHT | 4 | 4 | 0.823 | 0 |
| 2 | H2 | Legal Framework | HLPL | 4 | 4 | 0.829 | 0 |
| 3 | H3 | Social Influence | AHXH | 5 | 5 | 0.853 | 0 |
| 4 | H4 | Subjective Perception | NTCQ | 5 | 5 | 0.901 | 0 |
| 5 | H5 | Social Trust | LTXH | 5 | 5 | 0.851 | 0 |
| 6 | H6 | Consumer Trust | LTNTD | 5 | 5 | 0.814 | 0 |
| 7 | H7 | Online Purchase Intention | YDMH | 3 | 3 | 0.792 | 0 |
| | | Total | | 31 | 31 | | 0 |

### 4.3. Exploratory factor analysis EFA

Prior to conducting Exploratory Factor Analysis (EFA), the study first assessed the suitability of the data for factor analysis using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity for the group of independent variables. As shown in result, the KMO value was 0.885, which exceeds the minimum acceptable threshold of 0.50, indicating that the sample size was adequate for factor extraction. Additionally, the Bartlett's Test yielded a significance level of p = 0.000, confirming that the correlation matrix is not an identity matrix and is therefore appropriate for factor analysis (Hair et al., 2010). Furthermore, the Communalities of all variables were greater than 0.50, meeting the requirement for shared variance among indicators. This suggests that each observed variable adequately contributes to the explanation of the latent factors.

Regarding Total Variance Explained, the analysis revealed that the cumulative percentage of variance extracted by the factors was 66.852%, which surpasses the conventional threshold of 50%. This implies that approximately 66.85% of the total variance in the dataset is accounted for by the extracted factors, thereby validating the factor structure of the measurement model.

### 4.4. Confirmatory Factor Analysis (CFA) and Model Fit Evaluation

Confirmatory Factor Analysis (CFA) was conducted to assess the measurement model's fit with the empirical data. The results indicated that the CFA model demonstrated good fit, as evidenced by the Chi-square test ($\chi^2$) with a p-value greater than 0.05, suggesting that the model is not significantly different from the observed data.

Furthermore, key fit indices met conventional thresholds: the Tucker–Lewis Index (TLI) and the Comparative Fit Index (CFI) both exceeded 0.90, indicating an acceptable to excellent model fit (Tucker & Lewis, 1973; Hair et al., 2010, 2017, 2019). The Chi-square divided by degrees of freedom (CMIN/df) was 1.578, well below the recommended cutoff of 2.0, and the Root Mean Square Error of Approximation (RMSEA) was 0.041, well below the maximum threshold of 0.08, further supporting the model's fit.

Although the Goodness-of-Fit Index (GFI) was 0.897, slightly below the ideal value of 0.90, this is still considered acceptable given the sample size ($n = 346$), number of latent factors, and observed variables. Hair et al. (2010, 2019) and Chou and Bentler (1995) note that such thresholds should be interpreted flexibly, and a GFI value above 0.80 can be deemed acceptable under such conditions.

All factor loadings in the CFA were above the minimum threshold of 0.5, with the majority exceeding 0.7, indicating strong convergent validity. The CFA results confirmed unidimensionality, reliability, convergent, and discriminant validity across all constructs. In conclusion, the measurement model demonstrated acceptable fit and statistical validity, confirming that the proposed conceptual framework is empirically supported by the data.

### 4.5. Structural Equation Modeling (SEM)

The structural model was evaluated using Structural Equation Modeling (SEM) to assess the hypothesized relationships among latent constructs. The results from both data groups—sellers (businesses) and buyers (individual consumers)—demonstrated acceptable model fit, as indicated by commonly accepted indices, including CMIN/df, CFI, RMSEA, and GFI (Hair et al., 2010, 2019; Chou & Bentler, 1995).

For the seller dataset, the SEM fit indices were reported as CMIN = 620.053, df = 389, and a p-value $< 0.05$, suggesting a statistically significant yet acceptable model fit considering the sample size and model complexity. The CMIN/df ratio was well within the recommended threshold ($< 3.0$), and other indices (CFI, GFI, RMSEA) confirmed the model's suitability for further structural analysis, as shown in **Figure 2**.

As presented in **Table 3**, the estimation results for the full structural model showed that all remaining hypothesized paths retained in the final model were statistically significant, with p-values less than

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0.05, thus confirming their relevance at the 95% confidence level. This indicates that the theoretical model proposed in this study is empirically supported by the data from both business and consumer groups.

Therefore, the standardized regression weights derived from the SEM analysis are summarized in **Table 3**, and all corresponding hypotheses are accepted based on their statistical significance

**Table 3:** Hypothesis Testing Results from SEM Estimation

| *Hypothesis* | *Structural Path* | *Unstandardized Estimate* | *Standardized Estimate (β)* | *S.E.* | *C.R.* | *p-value* | *Conclusion* |
|---|---|---|---|---|---|---|---|
| H1 | LTNTD ← NTCQ | 0.134 | 0.152 | 0.067 | 1.984 | 0.047 | Accepted |
| H2 | LTNTD ← LTXH | 0.097 | 0.127 | 0.040 | 2.427 | 0.015 | Accepted |
| H3 | LTNTD ← AHXH | 0.136 | 0.172 | 0.043 | 3.184 | 0.001 | Accepted |
| H4 | LTNTD ← CSHT | 0.130 | 0.128 | 0.056 | 2.313 | 0.021 | Accepted |
| H5 | LTNTD ← HLPL | 0.435 | 0.455 | 0.079 | 5.528 | < 0.001 | Accepted |
| H6 | YDMH ← LTNTD | 0.808 | 0.740 | 0.085 | 9.478 | < 0.001 | Accepted |

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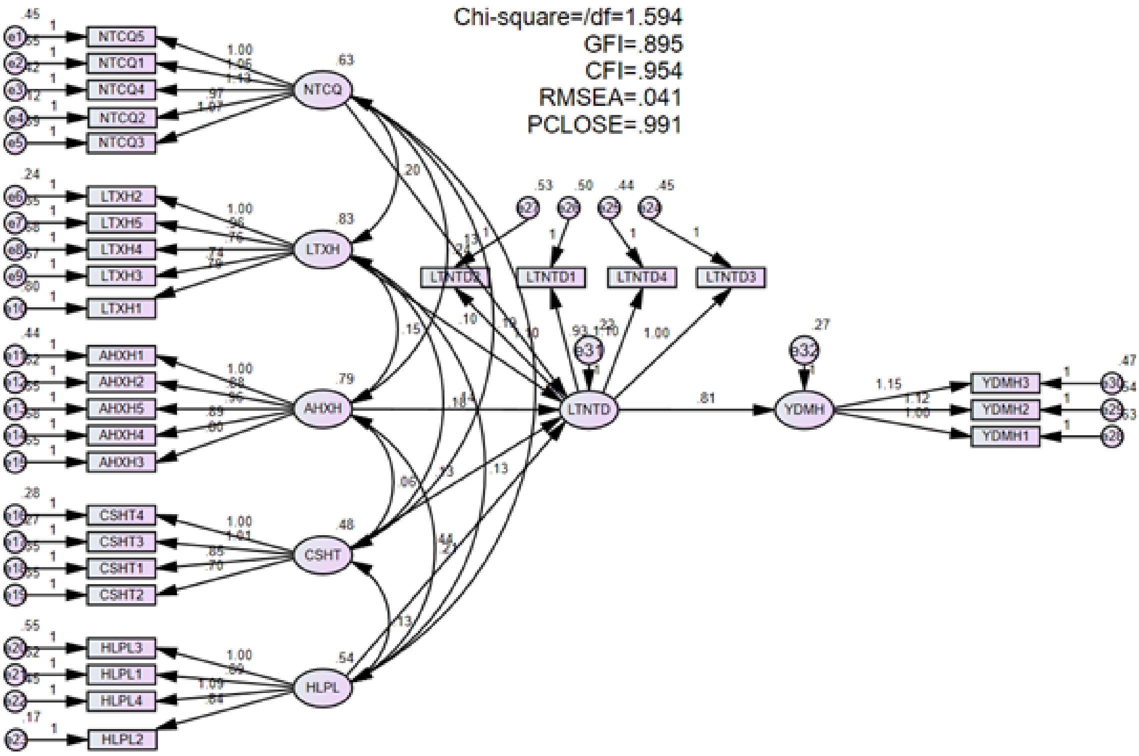


**Figure 2**. Result of SEM

**4.6. Discussion of the Research Model Results**

The findings obtained through the statistical analysis conducted via SPSS and AMOS indicate that the application of DeepFake technology in digital marketing is significantly influenced by a range of antecedent factors. These include: Technological Infrastructure (CSHT), Social Trust (LTXH), Social Influence (AHXH), Subjective Perception (NTCQ), Legal Framework (HLPL), and Consumer Trust (LTNTD). These constructs serve as intermediary variables, which in turn exert a significant impact on the dependent variable, Online Purchase Intention (YDMH).

Preliminary assessments of the measurement scales used in the study reveal that all independent constructs - CSHT, LTXH, AHXH, NTCQ, HLPL, and LTNTD - achieved Cronbach's Alpha coefficients greater than 0.60, satisfying the reliability threshold recommended by Hair et al. (2010). Following this, an Exploratory Factor Analysis (EFA) was performed, and the results confirmed the presence of seven distinct factor groups, which were retained for Confirmatory Factor Analysis (CFA).

The results of CFA further validated that all constructs exhibited unidimensionality, convergent validity, internal consistency, and discriminant validity. These findings provide strong psychometric support for the measurement model. In alignment with the theoretical framework, the study proceeded to test the proposed hypotheses through Structural Equation Modeling (SEM).

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The SEM results demonstrated that all hypothesized paths were statistically significant at the 95% confidence level ($p < 0.05$). Standardized regression weights confirmed the relevance and strength of each relationship. Among the predictors, Consumer Trust (LTNTD) emerged as the most influential factor affecting Online Purchase Intention (YDMH), with a standardized coefficient (β) of 0.740, indicating a strong direct effect. This finding is consistent with prior studies emphasizing trust as a key determinant of e-commerce behavior (Pavlou, 2003; Gefen et al., 2003; Hajli et al., 2014).

Furthermore, the inclusion of Legal Framework (HLPL) and Technological Infrastructure (CSHT) in the model reflects the growing concern about ethical and legal implications of AI-generated content, especially in contexts where DeepFake technologies may alter perceived authenticity. The impact of Social Influence (AHXH) and Subjective Perception (NTCQ) also reinforces the role of psychological and peer-based evaluations in forming trust, aligning with the Theory of Planned Behavior (Ajzen, 1991) and extended models of technology acceptance (Venkatesh et al., 2012).

In conclusion, the research model demonstrates strong empirical validity and theoretical robustness in explaining consumer responses to DeepFake-enhanced digital marketing. The high explanatory power of consumer trust underscores its central role in bridging the gap between advanced AI content and actual online purchasing behavior, particularly in the context of retail systems utilizing social media platforms.

## 5. CONCLUSION AND IMPLICATIONS

In the era of digital transformation, DeepFake technology has emerged as a pivotal and complex factor within the landscape of digital marketing, significantly shaping consumer perceptions and trust. This study demonstrates that consumer trust is no longer formed solely based on the quality or appeal of advertising content, but is rather influenced by a multifaceted system of interrelated factors, encompassing technological, legal, psychological, and social dimensions (Floridi et al., 2022; Tussyadiah, 2020).

Technological infrastructure plays a foundational role in the construction of consumer trust. Advances in DeepFake detection technologies have enabled consumers to better distinguish between authentic and manipulated content, thereby mitigating concerns about the verifiability and authenticity of advertising. According to the survey results, 78% of respondents emphasized the importance of integrating DeepFake detection tools into marketing platforms as a key criterion for verifying advertising credibility. These findings align with previous literature that highlights the role of technological transparency in enhancing digital trust (Kim et al., 2020).

The legal framework emerged as the strongest influencing factor on consumer trust in DeepFake-enabled marketing. The implementation of clear and enforceable regulations on AI and synthetic media use in advertising, alongside appropriate penalties for misuse, can serve as critical deterrents to unethical practices (HLEG AI, 2019). Remarkably, 85% of survey participants indicated that they would place more trust in advertisements if the use of DeepFake was explicitly regulated. This supports previous findings that regulatory mechanisms are essential for building trust in emerging AI applications (Binns et al., 2018; OECD, 2021).

Social influence was also validated as a significant determinant of trust. Information shared within one's social networks, feedback from peers, and endorsements from Key Opinion Leaders (KOLs) contribute to the formation of consumer perceptions and affect trust levels. The study found that 72% of respondents are more likely to trust advertising content when it is positively endorsed by friends or online communities. This reflects prior findings in the Theory of Social Influence and electronic word-of-mouth (eWOM) literature (Cheung & Thadani, 2012; Venkatesh et al., 2012).

Individual consumers' subjective perceptions, especially their self-assessed ability to detect DeepFake contentm, also play a significant role. The study found that consumers with higher awareness of DeepFake technology tend to be more skeptical and cautious in evaluating online content, while those with limited understanding are more susceptible to manipulation. Notably, 68% of consumers admitted to doubting the authenticity of advertisements when they were uncertain about the content's origin. These findings highlight the need for digital literacy initiatives and reinforce the notion that perceived information credibility is closely tied to cognitive evaluations (Metzger & Flanagin, 2013).

The dimension of social trust, which captures the public's overall confidence in brands and institutions, was identified as another critical construct. Brands that are perceived as credible and transparent in their use of AI and DeepFake technologies were significantly more likely to be trusted. In fact, 79% of respondents expressed a willingness to trust brands that disclose how they use such technologies in marketing communications. This is consistent with the growing demand for algorithmic transparency and ethical AI deployment (Zhou et al., 2021; Mittelstadt, 2019).

Crucially, the study confirms that consumer trust acts as a mediating variable that directly affects online purchase intention. When consumers trust both the brand and the content, they demonstrate a higher propensity to engage in purchase behavior. According to the data, 74% of respondents indicated they would purchase a product if they trust the advertising content and brand reputation. This reinforces earlier findings by Pavlou (2003) and Hajli et al. (2014), who asserted that trust is a cornerstone of consumer behavior in digital environments.

**Implications for Businesses**

Companies should adopt clear, honest, and proactive communication practices when deploying DeepFake and other AI-driven technologies in marketing campaigns. Transparency about how content is generated, including disclaimers when synthetic media is used, can help reduce consumer skepticism and foster long-term trust. This aligns with the growing consumer demand for ethical AI usage and brand accountability (Mittelstadt, 2019).

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Organizations should allocate resources toward the integration of DeepFake detection systems, which can authenticate marketing content before it is released to the public. Collaborating with independent verification bodies or digital certification platforms will further enhance content credibility and mitigate reputational risks. This approach reflects the best practices in AI governance and risk mitigation (Floridi et al., 2022).

To reinforce trust and adaptability, businesses should implement real-time feedback channels, such as in-app surveys, AI-driven chat support, and user rating systems. These mechanisms not only allow for dynamic response to consumer concerns but also contribute to a participatory model of marketing in which trust is co-created with the audience (Hajli et al., 2014).
Partnering with trusted Key Opinion Leaders (KOLs) and social media micro-communities can generate authentic social endorsement. When influencers transparently engage with AI-generated content and explain its nature, they act as cultural mediators who help translate technical complexity into accessible narratives, thus enhancing trustworthiness (Cheung & Thadani, 2012).

**Implications for Policy Makers and Regulators**
Governments and regulatory bodies must introduce and enforce well-defined legal frameworks that govern the ethical use of synthetic media in commercial contexts. Such regulations should clearly delineate boundaries regarding consent, data usage, content labeling, and liability for manipulation. Precedents such as the EU's Artificial Intelligence Act offer a valuable template (European Commission, 2021).

Public institutions should prioritize national awareness programs that equip consumers with the knowledge to identify, assess, and critically engage with DeepFake content. Digital literacy campaigns should be integrated into school curricula, public service media, and online platforms, especially targeting vulnerable populations who may lack the tools to verify online information (Metzger & Flanagin, 2013).

Policymakers should invest in interdisciplinary research initiatives that explore the implications of AI and DeepFake in digital communication. Additionally, they should support the development of industry-wide ethical standards, encourage cross-sector collaboration, and provide funding for open-source detection tools. This effort is crucial for achieving algorithmic transparency, fairness, and accountability in AI applications (HLEG AI, 2019; Zhou et al., 2021).

In the context of digital transformation, this study highlights the critical role of DeepFake technology as both a disruptive force and an opportunity in digital marketing, with consumer trust emerging as the central mediating factor influencing online purchase intention. Trust is shaped not merely by content aesthetics but by an interconnected system of technological infrastructure, legal safeguards, social influence, subjective perception, and institutional transparency. The findings emphasize that regulatory clarity and the adoption of DeepFake detection tools are essential for mitigating manipulation risks and restoring consumer confidence. Strategic collaboration with influencers, transparent AI disclosure, and robust consumer engagement mechanisms are recommended for businesses seeking to build sustainable trust. Meanwhile, policymakers must prioritize legal frameworks, digital literacy, and research investment to ensure ethical deployment of synthetic media technologies in commercial communication

## REFERENCES

[1] Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

[2]Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2018). 'It's reducing a human being to a percentage': Perceptions of justice in algorithmic decisions. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, 1–14. https://doi.org/10.1145/3173574.3173951

[3]Castelfranchi, C., & Falcone, R. (1999). Trust and control: A dialectic link. Applied Artificial Intelligence, 14(8), 799–823.

[4]Chae, H., Lee, Y., & Park, J. (2023). The dynamics of social trust and online content credibility in the age of deepfakes. Journal of Interactive Marketing, 61, 75–88. https://doi.org/10.1016/j.intmar.2023.01.004

[5]Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. Decision Support Systems, 54(1), 461–470. https://doi.org/10.1016/j.dss.2012.06.008

[6]Chou, C. P., & Bentler, P. M. (1995). Estimates and tests in structural equation modeling. In R. H. Hoyle (Ed.), Structural equation modeling: Concepts, issues, and applications (pp. 37–55). SAGE Publications.

[7]Damian, R. (2012). The history of digital marketing. Digital Marketing Journal, 5(3), 23–31.

[8]Dave, C., & Ellis, D. (2018). Digital marketing: Strategy, implementation and practice (7th ed.). Pearson.

[9]Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

[10] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Schafer, B. (2022). AI and the manipulation of trust: DeepFakes and consumer decision-making. AI & Society, 37, 45–54. https://doi.org/10.1007/s00146-021-01259-5

[11] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

[12] Giddens, A. (1996). The consequences of modernity. Stanford University Press.

[13] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Pearson Education.

[14] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Sage Publications.

[15] Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2019). PLS-SEM or CB-SEM: Updated guidelines on which method to use. International Journal of Multivariate Data Analysis, 1(2), 107–123.

[16] Hajli, N., Lin, X., Featherman, M., & Wang, Y. (2015). Social word of mouth: How trust develops in the market. International Journal of Market Research, 57(5), 673–689. https://doi.org/10.2501/IJMR-2015-070

[17] Hajli, N., Sims, J., Zadeh, A. H., & Richard, M. O. (2014). A social commerce investigation of the role of trust in a social networking site on purchase intentions. Journal of Business Research, 67(11), 2067–2074. https://doi.org/10.1016/j.jbusres.2014.04.004

[18] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

[19] HLEG AI. (2019). Ethics guidelines for trustworthy AI. European Commission. https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

[20] Kim, J., & Peterson, R. A. (2021). Trust in digital environments: The role of social cues and networks. Journal of Consumer Behaviour, 20(5), 1155–1170. https://doi.org/10.1002/cb.1934

[21] Kim, Y., Park, J., & Choi, J. (2020). Transparency and trust in human-AI interaction: The role of explanation and agency. Computers in Human Behavior, 107, 106431. https://doi.org/10.1016/j.chb.2020.106431

[22] Kingsnorth, S. (2016). Digital marketing strategy: An integrated approach to online marketing. Kogan Page.

[23] Kotler, P., & Armstrong, G. (2009). Principles of marketing (13th ed.). Prentice Hall.

[24] Liu, X., Guo, X., Wu, H., & Vogel, D. (2022). How influencers shape trust in emerging technologies: The case of DeepFake marketing. Journal of Interactive Marketing, 58, 1–17. https://doi.org/10.1016/j.intmar.2022.05.001

[25] Luo, Y., Xie, X., & Liu, C. (2023). Understanding consumer skepticism and trust in AI-generated content. Computers in Human Behavior, 138, 107432. https://doi.org/10.1016/j.chb.2022.107432

[26] McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. Academy of Management Review, 23(3), 473–490. https://doi.org/10.5465/amr.1998.926622

[27] McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. Information Systems Research, 13(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

[28] Metzger, M. J., & Flanagin, A. J. (2013). Credibility and trust of information in online environments: The use of cognitive heuristics. Journal of Pragmatics, 59, 210–220. https://doi.org/10.1016/j.pragma.2013.07.012

[29] Mika, P. (2019). Deepfake: Between innovation and manipulation. Journal of Media Ethics, 34(2), 102–110.

ISSN 2581-5148

Vol. 8, Issue.3, May-June 2025, p no. 313-332

[30] Mittelstadt, B. D. (2019). Principles alone cannot guarantee ethical AI. Nature Machine Intelligence, 1(11), 501–507. https://doi.org/10.1038/s42256-019-0114-4

[31] Mohammadi, S., Pashang, S., & Yaghoubi, N. M. (2022). Collective trust, social media, and misinformation: A structural equation approach. Telematics and Informatics, 71, 101835. https://doi.org/10.1016/j.tele.2022.101835

[32] Nguyễn Quý Thanh, & Nguyễn Thị Khánh Hòa. (2013). Lòng tin trong quan hệ xã hội và niềm tin cá nhân: Một phân tích lý luận. Tạp chí Khoa học Xã hội Việt Nam, 10(3), 45–56.

[33] OECD. (2021). OECD principles on artificial intelligence. https://www.oecd.org/going-digital/ai/principles/

[34] Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

[35] Saiyad, A., & Vivek, A. (2022). Understanding Deepfake architecture: Threats and countermeasures. AI & Society, 37(1), 133–148.

[36] Shin, D., & Park, Y. J. (2020). Social influence and trust in AI-mediated marketing content. Journal of Business Research, 116, 74–83. https://doi.org/10.1016/j.jbusres.2020.04.043

[37] Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. Psychometrika, 38(1), 1–10.

[38] Tussyadiah, I. P. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. Annals of Tourism Research, 81, 102883. https://doi.org/10.1016/j.annals.2020.102883

[39] Trần Hữu Quang. (2006). Lòng tin và vốn xã hội trong phát triển cộng đồng. Tạp chí Xã hội học, 3, 3–15.

[40] Vasist, A., & Krishnan, M. (2022). Deepfake detection and prevention: A review of recent advances. ACM Transactions on Multimedia Computing, Communications, and Applications, 18(3), 1–24.

[41] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

[42] Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412

[43] Võ Minh Sang. (2016). Lòng tin và niềm tin: Khái niệm và sự khác biệt. Tạp chí Tâm lý học, 12(2), 60–67.

[44] Zhou, Y., Wang, W., & Chang, V. (2021). Explainable artificial intelligence for effective decision-making in financial services. Computers in Human Behavior, 115, 106585. https://doi.org/10.1016/j.chb.2020.106585

[45] Zhu, D., Wang, H., & Li, Z. (2021). Trust formation in AI-powered marketing: The role of social consensus. Journal of Business Research, 129, 903–913. https://doi.org/10.1016/j.jbusres.2020.11.047