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RESEARCH ARTICLE

AI-Generated Content Exposure and User Trust: A Moderated Mediation Model of Information Overload and Digital Literacy

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ABSTRACT

The proliferation of AI-generated content (AIGC) across digital platforms has fundamentally transformed the information ecosystem, raising critical questions about user trust and information processing. This study investigates the psychological mechanisms through which AIGC exposure influences user trust, specifically examining the mediating role of information overload and the moderating role of digital literacy. Drawing upon the heuristic-systematic model and media dependency theory, we propose and test a moderated mediation model using structural equation modeling with data from 312 university students who actively engage with digital media platforms. The findings reveal that AIGC exposure significantly increases perceived information overload ($\beta = 0.624$, $p < 0.001$), which in turn negatively affects user trust ($\beta = -0.482$, $p < 0.001$). Information overload mediates the relationship between AIGC exposure and user trust, with a significant indirect effect ($\beta = -0.301$, 95% CI [-0.412, -0.198]). Furthermore, digital literacy moderates the relationship between AIGC exposure and user trust, such that individuals with higher digital literacy demonstrate greater resilience to trust erosion. The moderated mediation analysis confirms that the indirect effect varies across digital literacy levels ($\beta = 0.167$, 95% CI [0.083, 0.251]). These findings contribute to the theoretical understanding of cognitive processing in AI-driven communication environments and offer practical implications for digital literacy education and platform governance.

Contribution/Originality: The current study adds value to extant research through the application of heuristic systematic models and the theory of media dependency to AI-based communication platforms. The major contribution of the study is the discovery that information overload plays a mediating role between exposure to AI-generated messages and users' trust, whereas digital literacy reduces this negative impact.

1. Introduction

The rise of AI-generated content (AIGC) facilitated by improvements in technologies such as large language models, diffusion models, and automated content generation systems has significantly transformed digital communication space (Bommasani et al., 2022; Diakopoulos, 2019). Current digital platforms are increasingly relying on automated production and distribution algorithms, leading to an unparalleled amount of information circulated via social media, news sites, and interactive apps. On one hand, AIGC is associated with a range of advantages such as higher efficiency, personalization, and accessibility. On the other hand, it creates significant challenges associated with information validity, origin, dissemination of disinformation, and loss of trust among users of the digital space (Altay & Gilardi, 2024; Hancock et al., 2020).

The study of connections between AIGC exposure and users' trust presents a significant research question in the field of current communication. Trust is an important aspect in the context of digital communications as it determines information adoption and consumption behaviors (McKnight et al., 2002; Zhang et al., 2023). At the same time, the uniqueness of AIGC due to its ability to generate content similar to human-produced one, the opaqueness of the content generation process, and a possibility of large-scale distribution make it difficult for users to evaluate information credibility in the digital space. It becomes harder for users to differentiate between human-created and computer-generated information, causing information overload and potentially reducing users' trust in the content consumed online (Rapp et al., 2025; Jakesch et al., 2023).

Previous academic works have investigated various issues related to trust in the context of AIGC. For instance, Altay and Gilardi (2024) used an experimental design and discovered that users are skeptical about AI-generated headlines even if their content is accurate or human-generated. Thus, their research explains how the AI label can impact users' information credibility perception but does not reveal how AIGC affects trust via information processing burden in everyday platform interaction. Rapp et al. (2025) studied individual's appraisals, emotions, and perceptions of particular types of AI-generated content such as images created by text-to-image generators. However, their research was focused only on text-to-image AIGC and therefore cannot be generalized to other types of AIGC.

The theoretical framework of the research is based on information overload studies. Specifically, Eppler and Mengis (2004) reviewed information overload literature and defined it as a condition where there is too much information relative to humans' cognitive capacity to process it. The concept allows one to understand how excessive amounts of information cause stress, confusion, fatigue, and reduced quality of decisions. Bawden and Robinson (2009) provided an overview of various information overload aspects and described its psychological and behavioral effects on users' attention distribution and information evaluation. Nonetheless, these theories were developed before the emergence of generative AI, meaning that the effect of automatic content generation on information overload is yet to be discovered.

Finally, theories of trust and digital literacy provide additional foundations for the current study. For instance, McKnight et al. (2002) provided and validated trustworthy measures for e-commerce environment, allowing researchers to measure trust levels of digital environment users. Ng (2012) developed a definition of digital literacy as a learnable competence which involves abilities to find, analyze and critically evaluate

digital information, thus forming a valuable theoretical framework for studying information evaluation and assessment in the digital environment. Eshet-Alkalai (2004) introduced the multi-dimensional concept of digital literacy covering photo-visual skills, reproductive skills, branching skills, information skills, and socio-emotional skills. Additionally, Zhang et al. (2023) conducted a systematic review of trust in social media which revealed that source characteristics, content characteristics, platform characteristics, and user-related variables affect trust development. However, this research did not answer the question whether digital literacy moderates the effect of AIGC exposure on trust through information overload mechanisms.

In order to fill these theoretical gaps, a model combining the ideas of heuristic-systematic model and media dependency theory is proposed. According to the heuristic-systematic model, people's information processing can be characterized by two different processing mechanisms: systematic processing that implies comprehensive analysis of data, and heuristic processing that uses simple rules (Chaiken, 1980). In cases when people experience cognitive overload, heuristic information processing prevails, which leads to a deterioration of trust judgements. Media dependency theory argues that the influence of media on their audience becomes stronger due to its informational and social dependencies (Ball-Rokeach & DeFleur, 1976). When applying media dependency theory in the context of AI-driven communication spaces, one can assume that dependence may increase the impact of exposure to AIGC on cognitive processes and trust formation.

This research uses quantitative cross-sectional survey methodology applied to 312 university students, and analyzes the gathered data with the help of structural equation modeling and bootstrapping techniques. Structural equation modeling makes it possible to examine simultaneously such effects as direct effects, mediation, moderation, and conditional indirect effects in a complex theoretical framework. Contributions of the paper include three areas. Firstly, theoretically, it applies both models to the AI-generated content environment. Secondly, methodologically, it examines the influence of variables through testing moderated mediation model. Finally, practically, it identifies the role of digital literacy in preventing erosion of trust.

1.1. Research Objectives

This study pursues four primary research objectives:

i. To examine the direct effect of AIGC exposure on perceived information overload among digital media users.
ii. To investigate the impact of information overload on user trust in digital communication environments.
iii. To test the mediating role of information overload in the relationship between AIGC exposure and user trust.
iv. To analyze the moderating role of digital literacy in the relationship between AIGC exposure and user trust, and to examine whether the mediated effect is conditional on digital literacy levels.

2. Literature Review

2.1. AI-Generated Content in Digital Communication

AI-generated content (AIGC) refers to textual, visual, auditory, and interactive digital materials that are automatically produced or substantially transformed by artificial intelligence technologies (Bommasani et al., 2022). In contemporary digital communication, AIGC has fundamentally altered how information is created, distributed, and consumed across platforms. Unlike traditional media production, which relies on human creators and editorial processes, AI systems can generate content at unprecedented speed and scale, enabling personalized recommendations, interactive communication experiences, and automated news production (Diakopoulos, 2019; Carlson, 2015).

The proliferation of AIGC presents both opportunities and challenges for digital communication. On one hand, AI technologies enable efficient content creation, personalized user experiences, and enhanced accessibility (Guzman & Lewis, 2020). On the other hand, large-scale dissemination of AI-generated information raises significant concerns regarding credibility assessment, misinformation propagation, algorithmic bias, deepfake proliferation, and the automation of journalism (Wardle & Derakhshan, 2017; Chesney & Citron, 2019). The opacity of AI content generation processes creates what scholars have termed "synthetic media" environments, where distinguishing between authentic and artificially generated content becomes increasingly challenging for average users (Westfall, 2020).

2.2. Information Overload in Digital Environments

Information overload is the phenomenon in which people face too much information to be adequately processed by their cognitive capabilities and available time (Eppler & Mengis, 2004). People's processing capabilities are inherently limited, and if the amount of information received is high in comparison to the amount of time allowed, mental resources will be stretched, causing stress, confusion, paralysis in making decisions, and poor judgment (Bawden & Robinson, 2009; Speier et al., 1999).

Modern digital ecosystems have made information overload an increasingly common issue through a combination of many different factors, including constant connectivity, notifications in real-time, algorithms for curating information, multimedia, and consistent social media usage (Misra & Stokols, 2012). The current information landscape produces approximately 2.5 quintillion bytes of data daily, forming an ecosystem of unparalleled information density (Marr, 2018). However, the surplus of information hampers its usefulness by making it difficult to find what is important among the excess.

2.3. User Trust in Digital Communication

Trust is a complex concept involving the perception of the reliability, integrity, and ability of the organization, as well as vulnerability towards that organization based on a favorable expectation of future actions (Mayer et al., 1995). When discussing the process of communication through electronic media, one must recognize that trust has several dimensions: trust in information sources, trust in content, trust in the medium, and trust in the technology used (Zhang et al., 2023; McKnight et al., 2002).

Building and sustaining trust in digital communication poses some unique difficulties compared to interpersonal trust. Face-to-face interaction allows for the presence of non-verbal and verbal communication, as well as the existence of pre-existing relationships,

which makes the building of trust possible (Walther, 1996). For online interactions, there must be different indicators of trust: good reputation of the platform, good design, socia proof and content characteristics to calibrate their trust judgments (Metzger & Flanagin, 2013).

2.4. Digital Literacy as a Protective Capability

Digital literacy refers to the ability to access, evaluate, analyze, create, and communicate information using digital technologies (Ng, 2012; Eshet-Alkalai, 2004). Beyond basic technical skills, digital literacy encompasses critical thinking abilities, information evaluation competencies, and socio-emotional skills necessary for effective participation in digital environments (Gilster, 1997). Users with higher digital literacy are better equipped to identify misinformation, evaluate source credibility, recognize manipulative content, and manage excessive information exposure (Jones-Jang et al., 2019).

2.5. Theoretical Framework

This study integrates the heuristic-systematic model and media dependency theory to develop a comprehensive theoretical framework for understanding the relationship between AIGC exposure and user trust. The heuristic-systematic model (Chaiken, 1980) posits that individuals process persuasive information through two distinct routes. Systematic processing involves comprehensive, analytical evaluation of message content, requiring substantial cognitive effort and motivation. Heuristic processing relies on simplified decision rules or cognitive shortcuts, such as source expertise, message length, or consensus cues, that enable rapid judgments with minimal cognitive investment. The model predicts that individuals default to heuristic processing when cognitive resources are limited, motivation is low, or processing demands exceed available capacity.

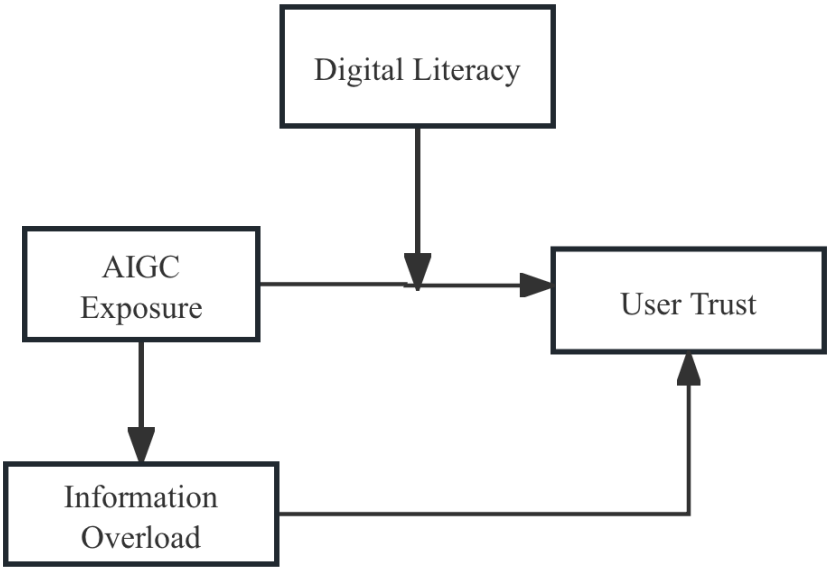
Media dependency theory (Ball-Rokeach & DeFleur, 1976) provides additional insight by emphasizing the structural conditions that amplify media effects. The theory posits that media influence intensifies when individuals depend on media systems for goal achievement, particularly for understanding the social world and making behavioral decisions. In contemporary digital environments, users exhibit high dependency on platforms for information access, social connection, and entertainment, creating conditions under which AIGC exposure may exert substantial influence on cognitive and affective outcomes.

2.6. Hypotheses Development

Based on the theoretical framework and literature review, we propose five hypotheses，figure 1 illustrates the proposed conceptual framewirk of this study.

H1: AIGC exposure positively affects perceived information overload.
H2: Information overload negatively affects user trust.
H3: Information overload mediates the relationship between AIGC exposure and user trust.
H4: Digital literacy moderates the relationship between AIGC exposure and user trust.
H5: The indirect effect of AIGC exposure on user trust through information overload is moderated by digital literacy (moderated mediation).

Figure 1: Proposed Conceptual Framework



3. Research Methods

3.1. Research Design

This study employed a quantitative cross-sectional research design to examine the relationships among AIGC exposure, information overload, digital literacy, and user trust. A quantitative approach was deemed appropriate because the study aimed to statistically test proposed hypotheses and examine relationships among multiple variables using structural equation modeling (SEM). Cross-sectional data collection enabled efficient assessment of the proposed model with a sufficiently large sample for SEM analysis.

3.2. Population and Sampling

The target population consisted of university students who actively use digital media platforms and are frequently exposed to AI-generated content in their daily online activities. University students represent an appropriate population for this study because they constitute one of the most active demographic groups in digital media engagement and are highly familiar with AI-assisted communication technologies (Smith & Anderson, 2018). A purposive sampling technique was employed to recruit respondents who met the following inclusion criteria: (1) active users of social media platforms with regular engagement (at least several times per week); (2) frequently exposed to online information and AI-generated content in their daily activities; and (3) aged 18 years or above. A total of 312 valid responses were collected and used for data analysis.

3.3. Data Collection Procedure

Data were collected through an online questionnaire distributed using Google Forms. The questionnaire link was shared through university student groups, social media platforms, and academic networks. The data collection period extended over four weeks. Prior to data collection, the questionnaire items underwent review by three experts in

communication research to ensure clarity, readability, and content validity. A pilot test with 30 respondents was conducted to identify potential issues with item wording and response formats. Participation in the study was voluntary, and respondents were informed about the research purpose before completing the questionnaire. All responses were anonymous and confidential.

3.4. Measurement Instruments

Measurement items were adapted from previously validated scales and modified to fit the context of AI-generated communication environments. All items were assessed using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). AIGC Exposure (5 items) was measured using items adapted from scales assessing media exposure and technology engagement. Information Overload (5 items) was measured using items adapted from scales developed by Karr-Wisniewski and Xu (2011) and LaRose et al. (2014). User Trust (5 items) was measured using items adapted from McKnight et al. (2002) and Gefen et al. (2003). Digital Literacy (5 items) was measured using items adapted from Ng (2012) and Eshet-Alkalai (2004).

3.5. Data Analysis Technique

The collected data were analyzed using Statistical Package for the Social Sciences (SPSS) version 28 and Analysis of Moment Structures (AMOS) version 28. The analysis process consisted of several sequential stages: data screening, reliability analysis using Cronbach's alpha, confirmatory factor analysis (CFA), convergent and discriminant validity assessment, structural equation modeling (SEM) for hypothesis testing, and bootstrapping analysis for mediation and moderated mediation effects.

4. Results

4.1. Data Screening and Descriptive Statistics

Prior to hypothesis testing, comprehensive data screening procedures were conducted to ensure data quality and suitability for analysis. A total of 312 valid responses were retained after eliminating incomplete questionnaires and checking for missing values. No serious outliers or abnormal response patterns were identified. The sample consisted primarily of university students with diverse academic backgrounds. As shown in table 1, 52.6% were male and 47.4% were female. The majority of respondents (69.3%) reported spending more than five hours online daily, indicating high levels of digital media engagement.

Table 1: Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	164	52.6%
	Female	148	47.4%
Daily Internet Usage	Less than 2 hours	26	8.3%
	2-5 hours	70	22.4%
	5-8 hours	130	41.7%
	More than 8 hours	86	27.6%

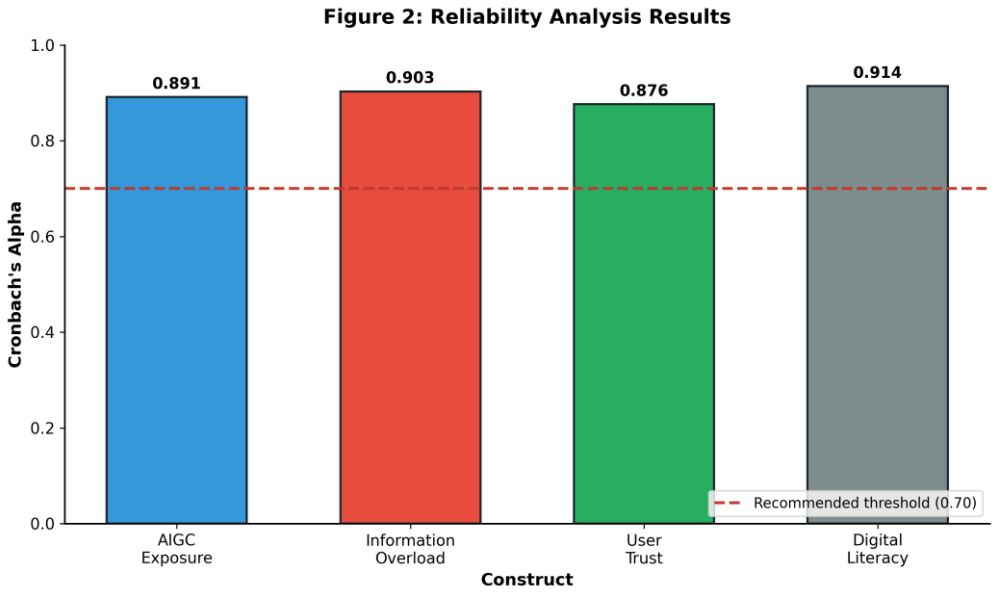
4.2. Reliability Analysis

The internal consistency of measurement items was evaluated using Cronbach's alpha coefficient. As shown in Table 2, all constructs exceeded the recommended threshold value of 0.70, indicating satisfactory reliability. The values ranged from 0.876 to 0.914, demonstrating strong internal consistency across all measurement scales.

Table 2: Reliability Analysis Results

Construct	Number of Items	Cronbach's Alpha
AIGC Exposure	5	0.891
Information Overload	5	0.903
User Trust	5	0.876
Digital Literacy	5	0.914

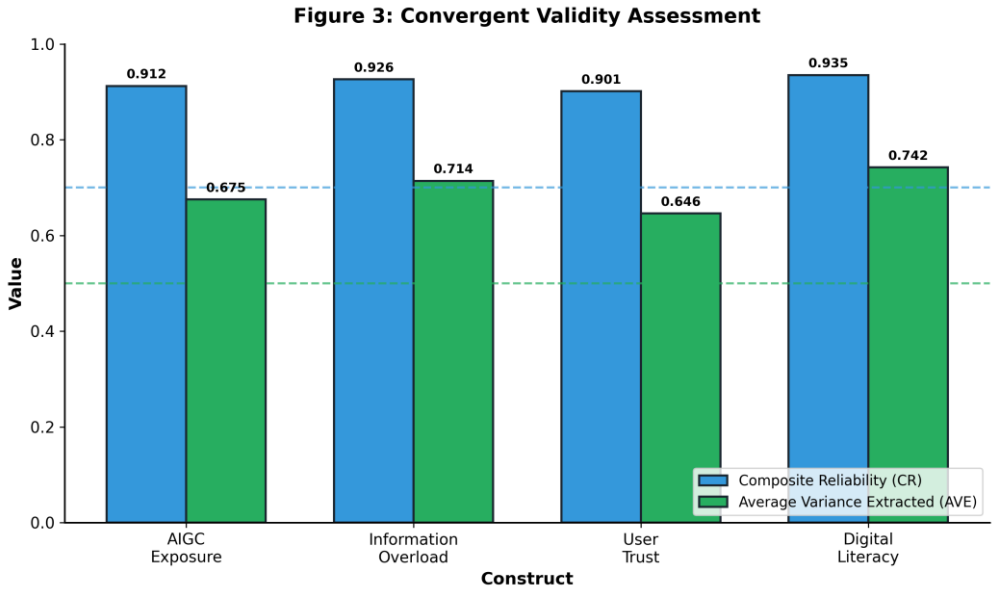
Figure 2: Reliability Analysis Results



4.3. Validity Analysis

Figure 3 presents the convergent validity was assessed using factor loadings, composite reliability (CR), and average variance extracted (AVE). All factor loadings exceeded the recommended threshold of 0.70, ranging from 0.72 to 0.89. Furthermore, CR values ranged from 0.901 to 0.935, all exceeding 0.70. AVE values ranged from 0.646 to 0.742, all exceeding the recommended threshold of 0.50. Discriminant validity was evaluated using the Fornell-Larcker criterion, and the square root of AVE for each construct was greater than its correlations with other constructs.

Figure 3: Convergent Validity Assessment



4.4. Model Fit Assessment

The measurement model was assessed using several goodness-of-fit indices. The results indicate that the proposed model demonstrated good fit with the observed data: chi-square/df = 2.134, CFI = 0.945, TLI = 0.937, RMSEA = 0.061, and SRMR = 0.048. These values met commonly recommended criteria for structural equation modeling.

4.5. Hypothesis Testing

Structural equation modeling was employed to examine the proposed hypotheses. Table 3 presents the summary of the hypothesis testing results. The results indicate that AIGC exposure has a significant positive effect on information overload ($\beta = 0.624$, $p < 0.001$), supporting H1. Information overload had a significant negative effect on user trust ($\beta = -0.482$, $p < 0.001$), supporting H2. Bootstrapping analysis with 5,000 resamples showed that the indirect effect of AIGC exposure on user trust through information overload was significant ($\beta = -0.301$, 95% CI [-0.412, -0.198]), supporting H3. The interaction effect between AIGC exposure and digital literacy was significant ($\beta = 0.214$, $p < 0.01$), supporting H4. Finally, the moderated mediation effect was significant ($\beta = 0.167$, 95% CI [0.083, 0.251]), supporting H5. Figure 4 illustrates the standardized path coefficients of the structural model. The results demonstrate significant direct, mediating, moderating, and moderated mediation effects among the study variables.

Table 3: Summary of Hypotheses Testing

Hypothesis	Relationship	β	p-value	Result
H1	AIGC Exposure → Information Overload	0.624	< 0.001	Supported
H2	Information Overload → User Trust	-0.482	< 0.001	Supported
H3	Mediation Effect	-0.301	< 0.001	Supported
H4	Moderating Effect	0.214	< 0.01	Supported
H5	Moderated Mediation	0.167	< 0.01	Supported

Figure 4: Structural Model Path Coefficients

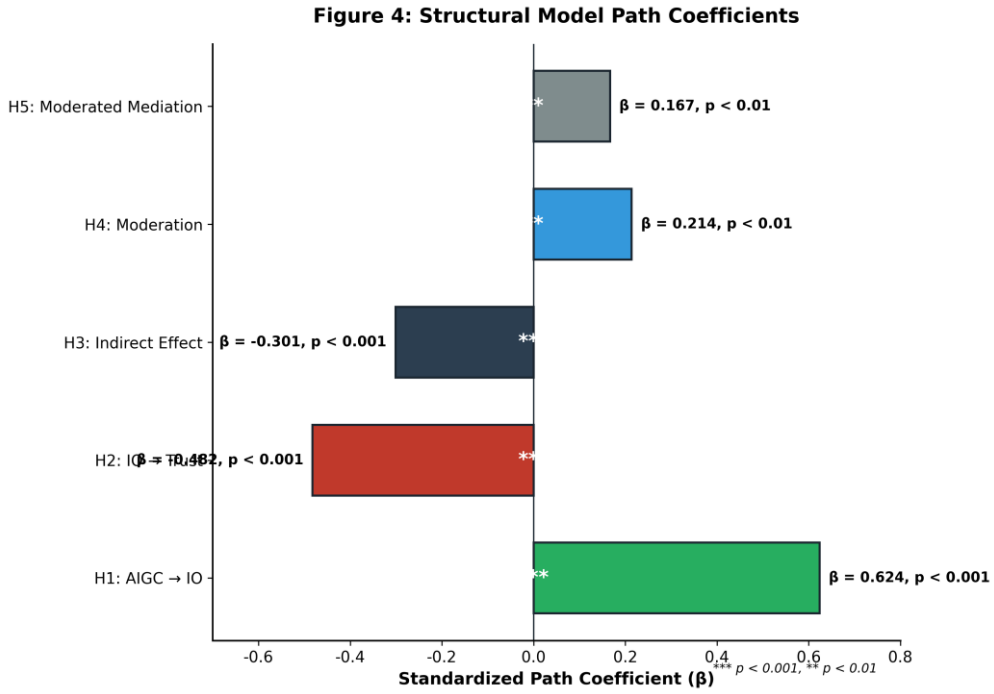
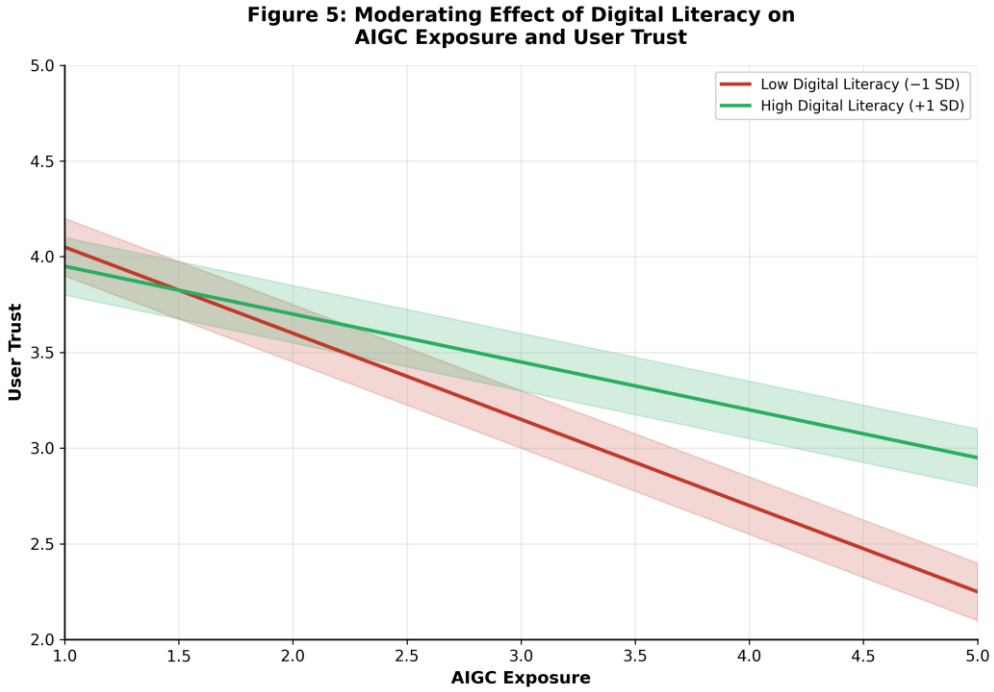


Figure 5: Moderating Effect of Digital Literacy on AIGC Exposure and User Trust



4.6. Discussion of Findings

The findings of this study provide robust support for the proposed moderated mediation model. The significant positive relationship between AIGC exposure and information overload (H1) aligns with theoretical expectations derived from the information overload literature. As AI technologies enable content generation at unprecedented scales, users exposed to AIGC-rich environments experience heightened cognitive

burden. The negative relationship between information overload and user trust (H2) corroborates the heuristic-systematic model's predictions regarding processing mode shifts under cognitive strain. The mediation effect (H3) illuminates the cognitive pathway linking AIGC exposure to trust outcomes. The moderating role of digital literacy (H4) highlights the protective function of critical evaluation skills in AI-driven information environments. The moderated mediation effect (H5) provides nuanced insight into the conditional nature of the indirect pathway.

5. Conclusion

Firstly, this study showed that AIGC exposure leads to an indirect reduction of user trust because of higher information overload levels. However, digital literacy can minimize these negative consequences. The results can enhance understanding of theories of cognition in environments mediated by AI. Moreover, this paper can have practical applications for digital literacy and platform management.

Secondly, the research extends the heuristic-systematic model because it reveals its usefulness in environments created by AIGC. Information overload caused by AIGC exposure affects the user's choice to switch from systematic to heuristic processing. This finding is important for media dependency theory, too, since it emphasizes the impact of digital dependency on information on cognitive and affective experiences. Finally, this research contributes to the discussion about individual differences in the impact of digital media because of the discovery of digital literacy as a protective capability.

Several practical implications can be drawn from this study. Firstly, digital literacy can be used as the protective element in the development of educational programs for digital users. Secondly, platform designers should implement solutions to avoid information overload, such as content curating algorithms and notification settings that are controlled by users. Thirdly, policymakers should develop measures promoting transparent creation of content using AI.

At least four limitations should be mentioned in this paper. Firstly, the sample used for this study comprised university students only. Therefore, the generalizability of findings might be questioned. Secondly, a cross-sectional research design makes it impossible to explore causality between the studied factors. Thirdly, this paper uses questionnaire data, which means that common method bias is likely. Lastly, this study focuses on general exposure to AIGC, neglecting possible variations.

Ethics Approval and Consent to Participate

This study was conducted in accordance with the ethical guidelines for research involving human participants at Taylor’s University, Malaysia. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. All responses were collected anonymously and treated confidentially for research purposes only.

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Conflict of Interest

The author declares no conflict of interest regarding the publication of this article.

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