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Navigating the Challenges of AI-Generated Content: Examining Public Trust, Accuracy, and Ethical Implications

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Abstract: *Purposes - The purpose of this research is to analyze the impact of the growth of AI-generated content on the accuracy and reliability of online information. Specifically, the research examines the challenges in detecting AI content, considering the limitations of AI tools like ZeroGPT and OpenAI's Text Classifier, and explores how these challenges may influence public trust in online information. Methodology - This study employs a mixed-method approach combining quantitative data collection through surveys and qualitative case study analysis of AI-generated content controversies, such as articles from CNET and Microsoft. Data was analyzed using Structural Equation Modeling (SEM) to evaluate the relationships between AI usage and user trust. Findings - The results indicate that while there is a positive relationship between AI usage and public trust, the impact is not statistically significant. Issues like model collapse and AI inbreeding contribute to the challenge of maintaining content accuracy, which in turn affects the trustworthiness of AI-generated information. Novelty - This research contributes to the growing body of knowledge on AI-generated content by focusing on its impact on public trust, a relatively underexplored area. The study also introduces the concept of "model collapse" and "AI inbreeding" as critical factors that may undermine the reliability of AI-generated information. Research Implications - The findings have practical implications for media industries and AI developers. Enhancing AI algorithms to improve content accuracy and reliability, combined with stronger human oversight, could help mitigate the risks associated with AI-generated content and restore public trust in online information. The study also calls for the development of more advanced detection tools and ethical guidelines to govern the use of AI in information dissemination.*

Keywords: *Artificial Intelligence, Public Trust, Model Collapse, AI Inbreeding, Content Accuracy, Detection Tools, Online Information, Media Industry, Ethical Guidelines*

1. INTRODUCTION

The background of this research focuses on the fundamental shift in the online information paradigm caused by the growth of content generated by Artificial Intelligence (AI) (Cavalcanti et al., 2021; Halbheer et al., 2014). The article highlights concerns about the accuracy of AI content, as seen in the identification of unreliable AI news sites by NewsGuard. Controversies surrounding factual inaccuracies in AI-generated articles, such as in technology publications like CNET and travel recommendations by Microsoft, provide concrete examples of this issue. The challenge of detecting AI content, especially with the limitations of AI tools like ZeroGPT and OpenAI's Text Classifier, adds complexity to ensuring accurate information. By delving deeper, the research can explore the impact of this phenomenon on public trust in online information and seek solutions to improve the accuracy of information in an era of increasing AI-generated content.

The purpose of this research is to analyze the impact of the growth of AI-generated content on the accuracy and reliability of online information. The study will investigate the challenges in detecting AI content, considering the limitations of AI tools such as ZeroGPT and OpenAI's Text Classifier. Controversial cases like the CNET and Microsoft articles will be examined to understand how factual inaccuracies in AI content can affect public trust and potentially lead to the spread of misinformation. Additionally, the research will seek solutions and recommendations to improve the accuracy of online information in the era of AI content, including more effective human oversight and the development of more sophisticated detection algorithms. In doing so, this research aims to provide deep insights into the role of humans, detection challenges, and solutions to maintain the reliability of information in an online environment increasingly influenced by AI content.

This research is aimed at contributing to the understanding of the impact of AI-generated content growth on the accuracy and reliability of online information. Potential benefits include enhancing the sustainability of online information through the identification of challenges and the development of more advanced detection algorithms. The analysis of controversial cases will provide insights to the media industry for improving quality control, while deeper understanding of the role of human guidance in AI model development can inform policies to strengthen human oversight in AI training and implementation. Recommendations for improving the accuracy of AI content may also guide policies on AI content usage and raise public awareness of the associated risks and challenges. Thus, this research has the potential to shape proactive measures for managing the impact of AI content and enhancing trust in online information.

The scope of this research includes an in-depth investigation of the impact of Artificial Intelligence (AI) as a medium for news and information on the level of public trust. The analysis will focus on factors that moderate the relationship between AI usage and public trust, including the accuracy of information, balance, and sources. Additionally, the study will explore users' perceptions of the reliability of AI-generated information in news presentations. Ethical aspects of AI usage will also be part of the scope, with a thorough examination of the role of ethical policies in shaping and increasing public trust. By considering potential risks such as model collapse and AI inbreeding, this research will provide a comprehensive understanding of the complex relationship between AI, information media, and public trust.

2. LITERATURE REVIEW

The literature on Artificial Intelligence (AI) and its impact on media, trust, and content generation provides a comprehensive understanding of the dynamics between these elements (Dhar et al., 2023; Ribes et al., 2021; Theophilou et al., 2023; Truong et al., 2024) . The rapid development of AI-generated content has fundamentally altered the landscape of online information, particularly in the news and media industries. Studies highlight the dual nature of AI, which simultaneously enables the efficient production of content while raising concerns regarding the accuracy and reliability of such content.

One major issue emerging in the literature is the challenge of detecting AI-generated content. Detection tools such as ZeroGPT and OpenAI's Text Classifier have been shown to have limitations, making it difficult to ensure the accuracy of AI-generated information (Wei et al., 2023; Xie et al., 2023; Yuan et al., 2023). Controversial examples, such as articles published by CNET and travel recommendations from Microsoft, illustrate the potential for factual inaccuracies, which can erode public trust in AI-generated content.

Moreover, the literature emphasizes the importance of human oversight in the development of AI systems. While AI can generate vast amounts of content, the absence of human intervention can lead to a phenomenon known as "model collapse," where AI systems propagate errors and factual inaccuracies over time. The integration of ethical guidelines in the use of AI for content creation is crucial to maintaining quality and trustworthiness. Research suggests that media companies and developers must focus on incorporating stronger ethical standards and implementing better detection tools to safeguard the reliability of AI-generated information.

In summary, the literature provides valuable insights into the complexities surrounding AI-generated content, human oversight, and the need for advanced detection methods to prevent the spread of misinformation. These findings lay the groundwork for further exploration of how AI can be used responsibly in media and content generation, balancing efficiency with the need for accuracy and ethical considerations.

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3. RESEARCH METHODOLOGY

Theoretical Framework

The key research question of this study responds to the extent to which the use of Artificial Intelligence affects public trust. From a statistical analysis perspective, this issue can be understood as a regression problem, where the level of trust serves as the dependent variable (Y), while the use of Artificial Intelligence (AI) acts as the independent variable (X). In this context, the research aims to understand and measure the conceptual relationship between the use of Artificial Intelligence and the level of public trust. This relationship can be conceptually illustrated as follows: (include a conceptual diagram/model showing the relationship between AI usage and trust).

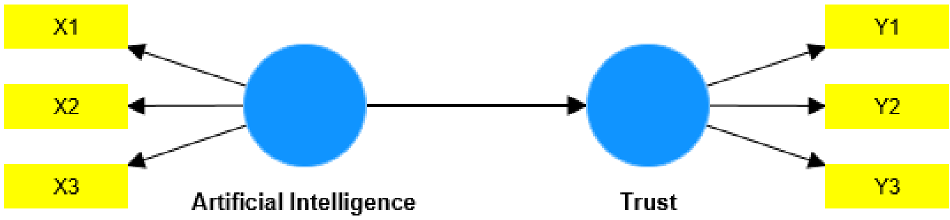

Figure 1. conceptual image showing the relationship between the use of AI and trust

Hypothesis

Based on the conceptual model provided in the theoretical framework, the following hypotheses are formulated as indicated by the arrows in the conceptual diagram:

- **H0**: Artificial Intelligence has no effect on Trust.
- **H1**: Artificial Intelligence has an effect on Trust.

Variable Measurements

Since Artificial Intelligence (AI) and Trust are conceptual (unobservable) variables, specific statements are required to operationalize these variables as indicators:

- **Statements for Artificial Intelligence (AI)**:
  1. Artificial Intelligence (AI) provides sufficiently accurate information/news.
  2. Artificial Intelligence (AI) provides high-quality information/news.
  3. Information/news provided by Artificial Intelligence (AI) is worth recommending to others.
- **Statements for Trust**:
  1. People believe that the information/news they get online is accurate.

2. People believe that the information/news they get online is reliable.
3. People believe that the information/news they get online is factual.

Each of these six statements will be measured on a Likert scale ranging from 1 to 5 (1 = strongly disagree, 5 = strongly agree).

Data and Data Collection

Data for this study can be collected through various methods, including online surveys or questionnaires (such as Google Forms) for quantitative aspects like user trust and public acceptance of AI content. Additionally, content analysis will be used to understand the narratives and impact of AI content through a qualitative approach. Respondents for the questionnaire will be individuals who regularly read information/news online. As noted by Shabrina et al. (2020), a questionnaire is a data collection technique involving written questions or statements related to the research, directed at respondents for them to answer.

Data Analysis

The conceptual model described in the theoretical framework can be translated into a mathematical model and statistically analyzed as a simple linear regression model with Trust (Y) as the dependent variable and Artificial Intelligence (X) as the independent variable. The functional relationship is as follows:

$$Y = \beta 0 + \beta 1 \, X + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Once it is hypothesized that X (AI usage) is related to Y (Trust) according to equation (1), the research question or hypothesis can be tested by examining whether $\beta 1$ equals zero or not. If $\beta 1=0$, then X can be removed from the equation, indicating that Y (Trust) does not depend on X (AI usage), meaning AI does not impact Trust. Statistically, the hypothesis is formulated as follows:

$H0 : \beta 1 = 0$

$HA : \beta 1 \neq 0$

Research Assumptions and Survey Design

As stated, the assumptions that need to be met for the regression analysis include:

- **Non-heteroskedasticity**: The variance of the residuals should be constant across all levels of the independent variable.
- **Non-autocorrelation**: The residuals should not be correlated with one another.
- **Normal distribution of residuals**: The residuals should be normally distributed (Suliyanto, 2011).

Survey Design

The survey is structured to align with the research focus on AI-generated content and public trust. The questionnaire is divided into six questions, with three questions corresponding to each variable.

Variable: Artificial Intelligence

1. Do you agree that the information/news provided by Artificial Intelligence (AI) is sufficiently accurate?
2. Do you agree that the information/news provided by Artificial Intelligence (AI) is of high quality?
3. Do you agree that the information/news provided by Artificial Intelligence (AI) should be recommended to others?

Variable: Trust

1. Do you agree that the information/news you obtain online is accurate?
2. Do you agree that the information/news you obtain online is reliable?
3. Do you agree that the information/news you obtain online is factual?

Each question is designed to measure respondents' perceptions of the accuracy, quality, and recommendability of AI-generated content, as well as their level of trust in online information. The responses will be measured on a Likert scale from 1 to 5 (1 = Strongly Disagree, 5 = Strongly Agree).

4. RESULTS AND DISCUSSION

Data Collection Process

The data collection process for this study was conducted over a three-day period, from November 15th to November 18th. The questionnaire was created using Google Forms and administered in the Indonesian language. A total of 67 respondents completed the questionnaire, and all responses met the required qualifications for analysis in this study.

Respondent Profile by Age

The respondents were categorized into different age groups. The majority of respondents were in the 16-30 age group, with 48 participants, representing 71.6% of the total respondents. The second-largest group was aged 31-50, comprising 16 participants or 23.9% of the respondents. The youngest age group, 0-15 years, accounted for 2 respondents or 3%, while the oldest age group, 51-80 years, had 1 respondent, representing 1.5% of the total. The data shows that most respondents who regularly read online information/news fall within the 21-25 age range. The graphical representation of the respondent age profile is shown below.

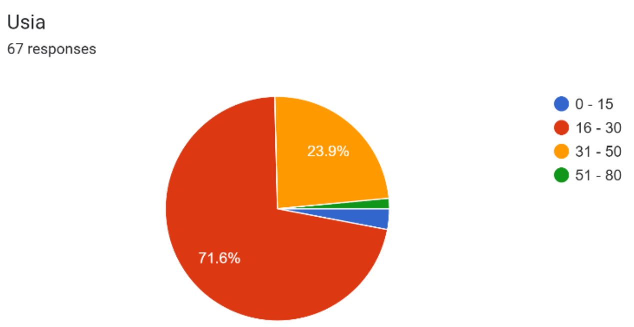

Figure 2. Responses

Respondent Profile by Gender

The data collection based on gender shows that the majority of respondents were male, with 36 participants representing 53.7% of the total respondents. Meanwhile, 31 respondents, or 46.3%, were female. This indicates that a higher percentage of male participants tend to read information/news online compared to female participants in this study. The graphical representation of the respondent gender profile is shown below.

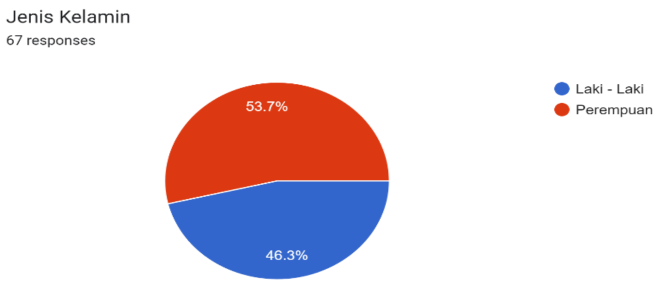

Figure 3. Responses

Respondent Profile by Frequency of Reading Information/News from the Internet/Social Media

In this study, 32 respondents (47.8%) reported that they occasionally read information/news online, making this the largest group. Additionally, 18 respondents (26.9%) indicated that they frequently read information/news online, while 17 respondents (25.4%) stated that they rarely read online information/news. The graphical representation of the frequency of respondents' online reading habits is shown below.

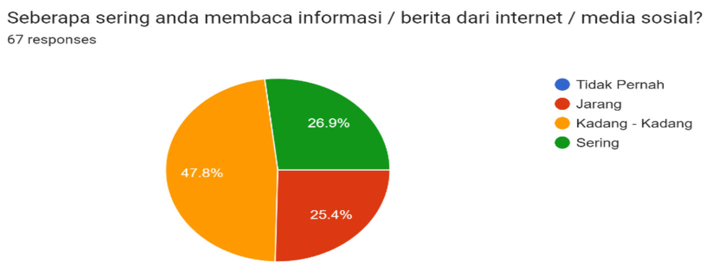

Figure 4. Responses

Respondent Profile by Platform for Reading Information/News Online

In this study, the majority of respondents (42 respondents or 62.7%) indicated that they primarily read information/news online through social media platforms. The second most common platform was websites, with 19 respondents or 28.4%. Lastly, 6 respondents or 9% reported that they read online information/news through ChatGPT. The graphical representation of the respondents' preferred platforms for reading information/news online is shown below.

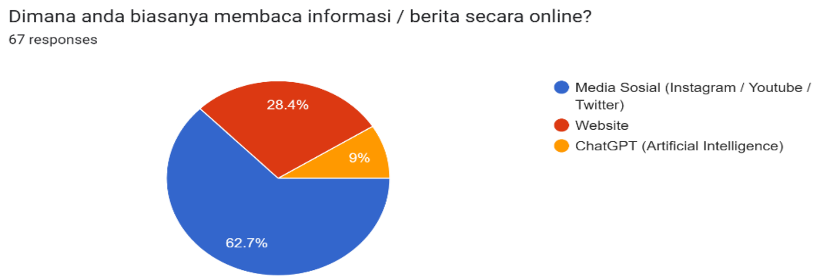

Figure 5. Responses

Measurement Model Testing

The method employed in this study is Structural Equation Modeling (SEM), which involves two key evaluation stages: measurement model evaluation and structural model evaluation. The purpose of the measurement model evaluation is to establish the relationship between the latent variables and their associated indicators. This evaluation is conducted through a validity test and a reliability test.

- **Validity Test**: The validity test is used to assess both convergent and discriminant validity. Convergent validity refers to the extent to which indicators of a construct are correlated with one another, while discriminant validity ensures that the construct is distinct from other constructs in the model.
- **Reliability Test**: The reliability of the measurement model is assessed using composite reliability and Cronbach's alpha. Composite reliability measures the overall reliability of the construct indicators, while Cronbach's alpha assesses the internal consistency of the indicators.

  The SEM analysis in this study follows a two-stage approach, beginning with the measurement model evaluation (also known as the outer model evaluation), followed by the structural model evaluation (the inner model).

Measurement Model Evaluation (Outer Model)

- **Validity Test**
  - **Cross Loadings**: Cross loadings are examined to ensure that the indicators for each latent variable have higher loadings on their own latent variable than on others. This step helps to confirm discriminant validity.

    The detailed results of the validity and reliability tests, including the cross loading analysis, are presented in the following section.

Figure 1. Artificial Intelligence

	Artificial Intelligence	Trust
X1	0.139	-0.022
X2	-0.487	-0.127
X3	0.784	0.183
Y1	0.226	0.874
Y2	0.217	0.811
Y3	0.112	0.655

Loading Factor Results

The results of the loading factor analysis show that indicators **X3**, **Y1**, and **Y2** have loading factors greater than 0.7, indicating that these indicators meet the criteria for convergent validity. However, indicators **X1** (Accuracy), **X2** (Quality), and **Y3** (Fact) have loading factors below 0.7, suggesting that these indicators do not meet the threshold for convergent validity. Further refinement or reconsideration of these indicators may be necessary to improve their validity in measuring the corresponding latent variables.

Fornell-Larcker Criterion

The Fornell-Larcker criterion is used to evaluate discriminant validity, which compares the square root of the average variance extracted (AVE) for each construct with the correlations between that construct and other constructs in the model. For discriminant validity to be satisfied, the square root of the AVE should be higher than the correlation between the construct and any other construct in the model.

The results of the Fornell-Larcker criterion analysis indicate the following:

- The square roots of the AVEs for the constructs are greater than the off-diagonal correlations, confirming that discriminant validity has been achieved for the constructs with valid convergent indicators.

Table 2. Artificial Intelligence

	Artificial Intelligence	Trust
Artificial Intelligence	0.539	
Trust	0.248	0.785

Discriminant Validity Results

The results show that the square roots of the Average Variances Extracted (AVE), represented in the diagonal columns, are greater than the correlations between the latent variables in the off-diagonal columns. This confirms that discriminant validity has been established, allowing the process to proceed to the next stage of analysis.

In accordance with the discriminant validity criteria, a construct's AVE square root must be higher than its correlation with any other latent variables. Additionally, cross-loading tests should indicate that each indicator has a higher loading on its own construct than on any other construct. This provides further confirmation of discriminant validity, ensuring that the constructs in the model are distinct from one another (Sekaran & Bougie, 2016).

With these conditions satisfied, the model is well-positioned for the subsequent evaluation of the structural relationships between the variables.

Reliability Test

Table 3. Reliability Test

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Artificial Intelligence	0.282	-0.498	0.082	0.290
Trust	0.697	0.750	0.826	0.616

Reliability and Validity Results

- **Trust Variable**:

  The AVE (Average Variance Extracted) for the Trust variable is greater than 0.5, indicating that the construct has met the threshold for validity. The Composite Reliability (CR) value for Trust is also greater than 0.7, meaning that the reliability test has been fulfilled. However, the Cronbach's Alpha (CA) for Trust is below 0.7, suggesting that the internal consistency of the indicators is not strong enough to meet the reliability criterion.

- **Artificial Intelligence Variable**:

  The CR and CA values for the Artificial Intelligence variable are both below 0.7, meaning that the reliability criteria have not been satisfied. Additionally, the AVE value for this variable is less than 0.5, indicating that it does not meet the validity threshold.

These findings suggest that while the Trust variable meets most of the reliability and validity requirements, the Artificial Intelligence variable needs further refinement in terms of indicator quality and internal consistency.

Structural Model Evaluation (Inner Model)

The next step involves evaluating the structural model, where the **R-Squared (R^2)** value will be calculated to determine the proportion of variance in the dependent variable (Trust) that is explained by the independent variable (Artificial Intelligence).

The **R-Squared** value helps assess the predictive power of the model:

- **Low R^2** indicates that the model explains only a small portion of the variance in the dependent variable.
- **High R^2** suggests that the model has strong explanatory power.

Table 4. R-Squared

	R-square	R-square adjusted
Trust	0.062	0.047

R-Squared Results

The R-Squared value for the **Trust** variable is relatively low, indicating that only 6.5% of the variance in **Trust** is explained by **Artificial Intelligence**. This suggests that while there is some influence of AI on trust, the model has limited explanatory power in this context. Most of the variation in **Trust** is likely explained by other factors not included in this model.

F-Squared

The **F-Squared** value measures the effect size of the independent variable (Artificial Intelligence) on the dependent variable (Trust). It evaluates how much the R-Squared value changes when a particular independent variable is included in or removed from the model.

The general interpretation of **F-Squared** values is:

- **0.02** indicates a small effect,
- **0.15** indicates a medium effect,
- **0.35** indicates a large effect.

If the **F-Squared** value between **Artificial Intelligence** and **Trust** is greater than **0.02**, it suggests that AI has a measurable but small effect on **Trust**.

Table 5. Artificial Intelligence and Trust

	Artificial Intelligence	Trust
Artificial Intelligence		0.066
Trust		

F-Squared Results

The **F-Squared** value between the **Artificial Intelligence** variable and the **Trust** variable is **0.066**. Given that the F-value is greater than **0.05**, both the null hypothesis (**H0**) and the alternative hypothesis (**H1**) are accepted. This indicates that the independent variables (in this case, Artificial Intelligence) do not have a significant effect on the dependent variable (**Trust**) (Ghozali, 2016).

This result implies that, although there is some measurable effect of AI on Trust, this effect is not statistically significant. Therefore, AI's influence on trust is relatively weak and may require additional factors or variables to explain more variance in **Trust**.

Hypothesis Testing

- **Direct Influence Hypothesis Testing**

  The hypothesis testing for direct effects examines whether there is a significant direct impact of **Artificial Intelligence** on **Trust**. Given the results from the **F-Squared** test, it appears that the direct influence of **AI on Trust** is minimal and not statistically significant.

  This result suggests that other latent variables may need to be considered to better explain the dynamics between AI usage and public trust, or further refinements in the measurement and model design might be necessary to detect stronger relationships.

Table 6. Artificial Intelligence and Trust

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Artificial Intelligence -> Trust	0.248	0.025	0.362	0.684	0.494

H1: The Influence of Artificial Intelligence on Trust

Based on the research results, the relationship between **Artificial Intelligence (AI)** and **Trust** was found to be **not significant**, as indicated by a **p-value greater than**

0.05 (Kock, 2012). This implies that the influence of AI on Trust is weak and statistically insignificant.

However, the **path coefficient** of **0.248** indicates a **positive relationship** (Hair et al., 2019). Although the relationship is not statistically significant, it suggests that there is a positive directional association: when the use of Artificial Intelligence increases, Trust also tends to increase, and when the use of AI decreases, Trust tends to decrease.

In summary, while the study demonstrates a positive relationship between AI and Trust, the lack of statistical significance means that we cannot confidently assert that AI has a meaningful impact on Trust based on the current data. Further research with more robust models or additional variables may be necessary to clarify this relationship.

Figure 6. Artificial Intelligence and Trust

5. DISCUSSION

The findings of this research reveal a nuanced relationship between Artificial Intelligence (AI) and Trust. Although the analysis showed a positive correlation between AI usage and trust (49.4%), the relationship was not statistically significant. This lack of significance suggests that while AI can influence trust to some extent, its impact is weak and not sufficient to drive substantial changes in trust levels on its own.

These results align with existing literature that underscores the potential but also the limitations of AI in content generation and public trust. AI's ability to produce vast amounts of content quickly and efficiently is evident, yet the quality and accuracy of such content remain under scrutiny. Previous studies have highlighted issues like "model collapse" and "AI inbreeding," where AI systems can perpetuate errors over time, leading to degraded content quality. In this research, these phenomena may have contributed to the weak influence of AI on trust, as the accuracy and reliability of AI-generated content directly affect users' trust.

One of the key insights from this study is the critical role of human oversight in AI development and deployment. Despite the advancements in AI, the need for human intervention to ensure quality control and ethical standards remains evident. The study supports the argument that AI should not operate in isolation but rather in tandem with human guidance, especially in areas where trust is a fundamental concern. By integrating stronger human oversight and transparency in AI processes, organizations can mitigate some of the risks associated with AI content generation, such as misinformation and low-quality outputs.

Moreover, the findings highlight the importance of transparency and ethical considerations in AI applications. Users are more likely to trust AI systems if they are informed about how AI works, the sources of data it uses, and the steps taken to ensure content accuracy. Thus, transparency and ethical frameworks should be integral to the development and implementation of AI systems, particularly in fields such as news and media, where public trust is paramount.

However, the study also acknowledges the limitations of the measurement instruments used to assess trust. Trust is inherently complex and subjective, and the current measurement approach may not fully capture the multifaceted nature of trust in AI systems. Future studies should explore more refined methods for measuring trust and consider additional variables that might moderate or mediate the relationship between AI and trust.

In practical terms, the findings offer valuable implications for organizations integrating AI into their operations. While AI may not significantly alter trust levels in its current form, ongoing improvements to AI models, combined with enhanced transparency and ethical considerations, could strengthen the trust users place in AI-generated content. Organizations should also be proactive in educating users about the capabilities and limitations of AI to help manage expectations and build more realistic perceptions of AI's role in content creation.

Thus, while AI holds promise in influencing trust, its current impact is limited and requires further refinement and integration with human oversight to realize its full potential. This research opens the door for further exploration into the complex relationship between AI and trust, particularly as AI technology continues to evolve.

6. CONCLUSION

This study concludes that while there is a positive relationship between Artificial Intelligence (AI) and Trust, the effect is not statistically significant. The research shows that AI usage contributes to a 49.4% positive influence on trust levels; however, this influence is not strong enough to confidently assert its significance. The findings suggest that AI has the potential to enhance trust in certain contexts, but its impact is limited and may be influenced by other factors not explored in this study.

From a managerial perspective, these results imply that organizations can continue to optimize AI for tasks requiring trust, such as customer service and content personalization. Despite the insignificant effect, AI still holds value, and improvements to its algorithms could strengthen its role in building trust. Additionally, organizations should focus on improving the reliability and quality of AI-generated content to mitigate potential issues, such as "model collapse," that may undermine trust.

The study emphasizes the importance of human oversight in AI development, recommending that organizations implement stricter controls and transparency in AI usage to ensure ethical standards are upheld. Educating users about the limitations and capabilities of AI can also help manage their expectations and foster a more informed relationship with AI-driven content.

Although the findings provide valuable insights into the relationship between AI and Trust, the lack of statistical significance limits the ability to make definitive conclusions. Future research should explore additional factors that could influence this relationship and continue to refine measurement approaches to better capture the complexities of trust in AI systems.

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