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# From Ethics to Impact: Modeling the Role of AI Perception Dynamics in the Relationship between Ethics AI Practices, AI-Driven Societal Impact, and AI Behavioral Analysis

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**Abstract**

The rapid evolution of Artificial Intelligence (AI) has brought about significant changes across various sectors, including healthcare, finance, and criminal justice, presenting both remarkable opportunities and complex ethical challenges. As AI becomes increasingly embedded in decision-making processes, concerns about individual rights, social equity, and public trust grow, particularly in high-stake contexts. These ethical implications underscore the critical need for robust frameworks that emphasize AI transparency, accountability, and fairness to mitigate risks such as bias and ensure responsible usage. Despite the increased focus on ethical AI practices, a considerable gap remains in the understanding of how these frameworks impact societal perceptions and behaviors toward AI. This study seeks to address this gap by investigating the effects of ethical AI practices, specifically transparency, accountability, and fairness, on public perceptions and behaviors. The study employs a quantitative approach using purposive sampling to select a sample of AI-knowledgeable participants and analyze the data using Partial Least Squares Structural Equation Modeling (PLS-SEM). This methodological approach allows for detailed exploration of the relationship between ethical AI practices and societal impacts. Additionally, this study examined the mediated pathways through which these ethical practices influence AI's societal and behavioral impacts, hypothesizing that transparency and accountability foster trust and positive engagement. By developing a framework that aligns ethical AI practices with societal values, this study aims to advance the broader goals of societal trust, public acceptance, and sustainable social integration of AI technologies. These insights contribute to a growing body of knowledge on responsible AI deployment, support ethical alignment in diverse AI applications, and promote the trustworthiness of AI-driven systems.

*Keywords:* ethical AI practices, AI perception dynamics, societal impact, behavioral analysis.

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## 1. Introduction

The rapid advancement of Artificial Intelligence (AI) has brought transformative changes to sectors such as healthcare, finance, and criminal justice, creating unprecedented opportunities while posing significant ethical concerns. As AI systems become integral to decision-making, they introduce critical issues related to individual rights, social equity, and public trust(David et al., 2024). Public perceptions of AI include mixed views, with many people recognizing its potential benefits but remaining cautious about the risks it may pose(Murphy et al., 2021). Research has shown that people with higher AI knowledge tend to have a more optimistic view of its usefulness, whereas those with limited understanding tend to feel apprehensive about its potential impact (Araujo et al., 2020). This indicates that increasing public knowledge and awareness of AI can help reduce fear and encourage a more informed discussion of the ethical application of AI (Oprea et al., 2024). In addition, the ethical aspects of AI are increasingly becoming a major concern in public discussion. As AI technologies become more integrated into everyday life, ethical issues such as transparency, accountability, and fairness become increasingly important. Recent literacies highlight the need for informed policies to address these ethical challenges and encourage public participation in AI-related decision-making processes (Samuel

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et al., 2024). These ethical considerations are particularly crucial in high-impact areas, where AI-driven decisions can significantly affect human lives and social structures**.** Consequently, establishing strong ethical frameworks is essential to ensure that AI systems function transparently and responsibly, helping to mitigate risks such as bias and uphold accountability (Morley et al., 2020).

However, despite the increased focus on ethical AI, there is still a notable gap in the understanding of how these frameworks impact societal attitudes and behaviors toward AI. Much of the current literature emphasizes the technical aspects of AI, often overlooking public trust and acceptance of these systems (Khairatun Hisan & Miftahul Amri, 2022; Fakhri et al., 2024; Vandamme & Kaczmarski, 2023). AI ethical guidelines at the global level, noting that while many guidelines encourage increased trust in AI, there are concerns that this excessive trust may reduce oversight and weaken the social responsibility of AI producers (Jobin et al., 2019). This study aims to address this gap by investigating how ethical AI practices, including transparency, accountability, and fairness, influence public perceptions and behaviors regarding AI technologies. By examining these dynamics, this study seeks to provide insights into how ethical principles shape user interactions and broader societal outcomes.

Recent literature further emphasizes that the inclusion of ethical principles, such as fairness, explainability, and non-discrimination, significantly shapes the way AI is perceived and utilized by individuals. For instance, studies have shown that ethical AI design fosters not only trust and compliance but also supports users in forming accurate mental models of how AI works, leading to better behavioral outcomes and societal impacts (Burr & Leslie, 2023; Felzmann et al., 2020; Pandey et al., 2024). Moreover, an inclusive and context-aware ethical framework helps ensure that the benefits of AI are distributed equitably across communities, enhancing both the engagement and legitimacy of AI systems in society(Friedler et al., 2019; Oluwaseun Augustine Lottu et al., 2024). These insights reinforce the urgency of embedding ethics in the entire AI lifecycle to responsibly and sustainably realize its potential.

This article aims to examine how ethical principles in AI, specifically transparency, accountability, and fairness, influence public trust, user behavior, and the broader societal acceptance of AI technologies. By investigating these relationships, this study seeks to contribute to the ongoing discourse on responsible AI, emphasizing the need to align AI development with ethical standards that are consistent with public values and social expectations. In doing so, the research also explores the mediating role of public perception in shaping how ethical design choices translate into behavioral and societal outcomes.

Based on this objective, this study addresses the following research questions:

a. How do ethical AI practices affect public perception of AI technologies?
b. To what extent do ethical AI practices directly influence AI-driven societal impact and AI-related user behavior?
c. Does the public perception of AI mediate the relationship between ethical practices and societal and behavioral outcomes?

## 2. Methods

### *2.1. Data Collection*

This study employed a quantitative, cross-sectional design using a one-time survey administered to a purposive sample of 375 participants from the Department of Informatics and Computer Engineering at Universitas Negeri Makassar. The purposive sampling strategy focuses on selecting participants with prior knowledge of artificial intelligence (AI), aiming to enhance the accuracy of responses related to the ethical, social, and behavioral implications of AI (Secinaro et al., 2021). Involving informed respondents is particularly important, as prior research indicates that they are better equipped to assess the complex impacts of AI across various sectors, such as healthcare and education. The chosen sample size adheres to recommended guidelines for Partial Least Squares Structural Equation Modeling (PLS-SEM), providing sufficient statistical power and ensuring reliable model estimation (Hair et al., 2019).

### *2.2. Instrumentation and measurement*

The research instrument consisted of items representing four key variables: AI Perception Dynamics (AIP), AI Driven Societal Impact (SI), AI Behavioral Analysis (BOA), and Ethics in AI Practices (EAI). Each item is rated on a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). To verify the reliability and validity of the instrument, analyses were performed using factor loadings, Cronbach’s alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Items with factor loadings above 0.7 were considered reliable, while Cronbach’s alpha and CR values greater than 0.7 indicated acceptable internal consistency (Nunnally & Bernstein, 1994). Additionally, an AVE value above 0.5 was considered necessary for convergent validity (Iqbal & Rao, 2023). Table 1 shows the aspect and item description of this research instrument.

**Table 1.** Aspects and item description

| Constructs | *Items Code* | Item Description |
|---|---|---|
| AI Perception Dynamics | AIPD1 | AI has the potential to have a positive impact on the field of work. |
| | AIPD2 | I feel confident that the development of AI can bring about positive changes in society. |
| | AIPD3 | AI can help solve complex problems more efficiently than humans. |
| | AIPD4 | I believe that the development of AI should be closely monitored to prevent negative consequences. |
| | AIPD5 | Although AI is developing rapidly, I am concerned about its impact on human jobs. |
| AI Driven Societal Impact | ADSI1 | I believe that the use of AI can improve efficiency in healthcare. |
| | ADSI2 | I understand the potential negative impact of AI on human employment. |
| | ADSI3 | I believe that AI implementation can help solve environmental problems. |
| | ADSI4 | I understand the ethics of using AI in everyday life. |
| | ADSI5 | I am aware of the social impact of AI technology development. |
| AI Behavioral Analysis | AIBV1 | I believe that AI's ability to understand and respond to human emotions can improve user experience. |
| | AIBV2 | I feel comfortable interacting with systems or applications that use AI. |
| | AIBV3 | I believe that the development of AI can change the way we interact with technology in the future. |
| | AIBV4 | I feel that AI can help predict and respond to user needs more effectively. |
| | AIBV5 | I believe that humans should retain full control over decisions made by AI systems. |
| Ethics AI Practices | EAIP1 | I understand the importance of ethical development and application in AI development. |
| | EAIP2 | I feel that transparency in the development of AI systems is important to ensure accountability. |
| | EAIP3 | I believe that the use of AI should be fair and equitable. |
| | EAIP4 | I believe that AI should not be used to manipulate information or public opinion. |
| | EAIP5 | I understand that data security aspects are very important in the development and use of AI. |

### *2.3. Data Analysis*

Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. PLS-SEM was chosen for its effectiveness in predictive analysis within exploratory research, especially for models with complex latent variables (Hair et al., 2019). The following procedures were conducted during data analysis:

- Reliability and Validity Assessment Internal consistency was evaluated using Cronbach's alpha, CR, and AVE to establish convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion, and Variance Inflation Factor (VIF) values were calculated to detect any multicollinearity issues among indicators (Chin, 1998).
- Structural Model Evaluation: The structural model was assessed based on path coefficients, R-squared values, and predictive relevance ($Q^2$). The significance of path coefficients was tested through bootstrapping (Chin, 1998)

## 3. Results and Discussion

### *3.1. Measurement of constructs*

Table 1 provides a detailed description of the items used to measure the four main constructs in this study: AI Perception Dynamics (AIPD), AI-Driven Societal Impact (ADSI), AI Behavioral Analysis (AIBV), and Ethics AI Practice (EAIP). Each construct contained several items specifically designed to represent the important aspects of the concept to be measured.

*3.2. Measurement Model*

Assessment of the reliability and validity of measurement instruments is an important element in Partial Least Squares Structural Equation Modeling (PLS-SEM)-based research. Evaluation of the outer model in PLS-SEM involves several key metrics to ensure the strength and accuracy of the construct measurement. In this study, metrics such as factor loading, Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and Variance Inflation Factor (VIF) were used to assess the reliability and validity of the measurement constructs, as presented in Figure 1, Table 2, and Table 3.

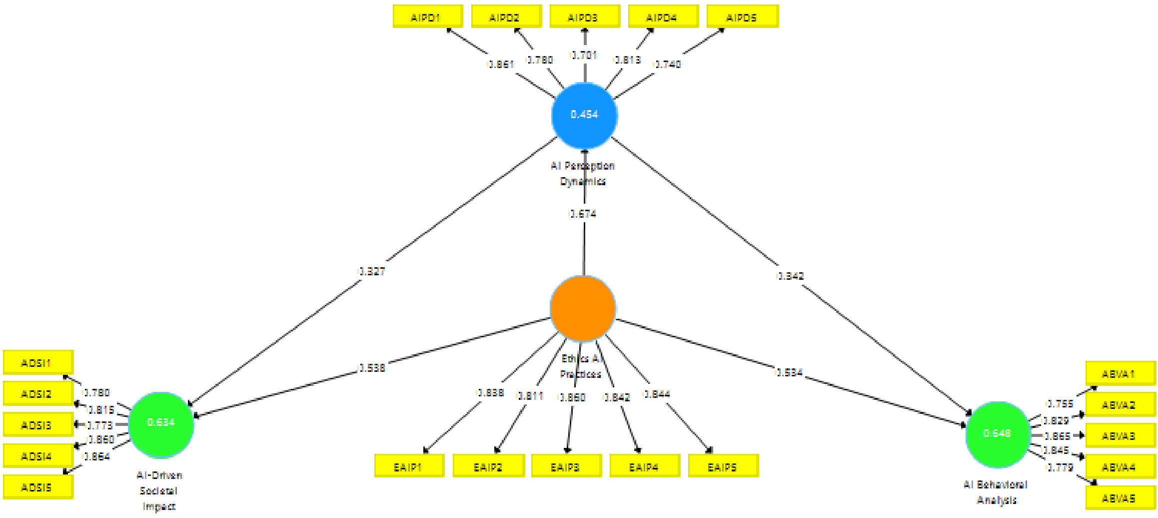


**Figure 1.** Outer Model

The figure 1 displays the structural model in Partial Least Squares Structural Equation Modeling (PLS-SEM) connecting the constructs of Ethical AI Practices, AI Perception Dynamics, AI-Driven Societal Impact, and AI Behavioral Analysis. This model shows how each construct in the study is interrelated, with indicators associated with each construct and path coefficients between constructs that reflect the strength of the relationship between latent variables. One of the fundamental indicators in this model is factor loading, which shows the strength of the relationship between each item and its latent construct. A factor loading value higher than 0.60 is considered to reflect a significant contribution of the item to the measured construct, thus indicating good indicator reliability (Mahaputra et al., 2023; Senna et al., 2023). In this study, all items show high factor loading, ranging from 0.85 to 0.94, which indicates that each item in the construct makes a strong contribution to the construct. This high value strengthens the overall construct validity and indicates that each indicator is truly relevant to the construct it represents.

To ensure that the constructs in the model produce consistent measurements, internal consistency reliability was assessed using Cronbach's alpha and CR. This reliability test aims to determine the extent to which items in each construct provide consistent results. Based on the data in Table 2, the Cronbach's alpha and CR values for all constructs are above the 0.70 threshold, which is a good indicator of reliability (Chang et al., 2020; Miran & Suhermin, 2023). For example, the Ethics AI Practices (EAIP) construct had the highest Cronbach's alpha value of 0.895, indicating excellent internal consistency between its items. The high CR value also confirms that all items in the construct are strongly correlated, meaning that the construct is truly reliable for measuring the intended concept.

Convergent validity, assessed through Average Variance Extracted (AVE), is a crucial metric in Partial Least Squares Structural Equation Modeling (PLS-SEM). This indicates the extent to which items within a construct can explain the variance of that construct. A commonly accepted threshold for AVE is 0.50, which signifies that the construct explains more than half of the variance of its indicators. Recent studies have reaffirmed this threshold, emphasizing its importance in establishing the reliability and validity of constructs in research (Atar & Atar, 2023; Mo et al., 2021). Based on the results presented in Table 2, all constructs in this study meet this criterion, with AVE values ranging from 0.610 to 0.704. Notably, the Ethics AI Practices (EAIP) construct exhibits the highest AVE value of 0.704, indicating that it effectively explains most of the variance contained in the related constructs. This finding confirms that each construct possesses sufficient convergent validity (Hossain et al., 2024).

In addition to convergent validity, it is essential to ensure that the constructs in this model do not suffer from multicollinearity issues. Variance Inflation Factor (VIF) is employed as an evaluation tool for this purpose. High multicollinearity can lead to interpretation challenges, as highly correlated items between constructs can obscure the unique influence of each construct (Oh, 2023). A VIF value below 5.0 is generally considered indicative of the absence of excessive multicollinearity(Bouchard-Bellavance et al., 2020; Judijanto et al., 2023). According to Table 2, the VIF values for each item range from 1.532 to 2.563, suggesting that there are no multicollinearity problems present in the data. This low VIF value ensures that each construct measures a unique dimension without excessive correlation between items, allowing for a more accurate interpretation of the relationships between constructs without redundancy (Munerah et al., 2021).

**Table 2.** Reliability and validity

| Statement | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE) | VIF |
|---|---|---|---|---|---|
| AIBV1 | | | | | 1.805 |
| AIBV2 | | | | | 2.382 |
| AIBV3 | 0.874 | 0.877 | 0.908 | 0.665 | 2.545 |
| AIBV4 | | | | | 2.347 |
| AIBV5 | | | | | 1.838 |
| ADSI1 | | | | | 1.860 |
| ADSI2 | | | | | 2.032 |
| ADSI3 | 0.877 | 0.885 | 0.911 | 0.671 | 1.835 |
| ADSI4 | | | | | 2.508 |
| ADSI5 | | | | | 2.563 |
| AIPD1 | | | | | 2.515 |
| AIPD2 | | | | | 2.124 |
| AIPD3 | 0.839 | 0.848 | 0.886 | 0.610 | 1.532 |
| AIPD4 | | | | | 2.184 |
| AIPD5 | | | | | 1.847 |
| EAIP1 | | | | | 2.186 |
| EAIP2 | | | | | 2.124 |
| EAIP3 | 0.895 | 0.896 | 0.922 | 0.704 | 2.499 |
| EAIP4 | | | | | 2.409 |
| EAIP5 | | | | | 2.456 |

**Table 3.** Fornell–Larcker criterion

| | AI Behavioral Analysis | AI Perception Dynamics | AI-Driven Societal Impact | Ethics AI Practices |
|---|---|---|---|---|
| AI Behavioral Analysis | 0.816 | - | - | - |
| AI Perception Dynamics | 0.702 | 0.781 | - | - |
| AI-Driven Societal Impact_ | 0.816 | 0.690 | 0.819 | - |
| Ethics AI Practices | 0.764 | 0.674 | 0.759 | 0.839 |

Discriminant validity is another critical aspect that ensures each construct in the model is substantially different from one another. Discriminant validity was evaluated using the Fornell-Larcker criterion, as shown in Table 3. This criterion stipulates that the square root of the AVE of each construct should be greater than the correlation of that construct with other constructs, ensuring that the construct is more closely related to its own indicators than to other constructs (Jamal et al., 2023; Moriña-Vázquez et al., 2021). Based on Table 3, all constructs meet the Fornell-Larcker criteria, indicating strong discriminant validity. This is vital because discriminant validity ensures that the constructs in the model measure distinct and unique concepts, preventing any conceptual overlap among the tested constructs.

Overall, the external model evaluation in PLS-SEM involving factor loading, Cronbach's alpha, CR, AVE, and VIF shows that the measurement instruments used in this study have met the reliability and validity standards. The high values of factor loading, Cronbach's alpha, CR, and AVE indicate that the constructs in this model are internally consistent and reliable in their measurement. In addition, the low VIF value ensures that there is no multicollinearity problem, so that each construct stands alone without excessive correlation between items. Meeting the Fornell-Larcker criterion also ensures strong discriminant validity, which confirms that each construct is significantly different from the other constructs. Thus, the overall measurement instrument used in this study can be considered reliable and valid, thus increasing confidence in the research results obtained through this PLS-SEM analysis.

### *3.3. Structure Model*

The structural model provides a deep understanding of the relationships between Ethics in AI Practices, AI Perception Dynamics, AI-Driven Societal Impact, and AI Behavioral Analysis, as shown in Table 4 and Figure 3. The hypothesis test results displayed in the table, alongside the visual representation in the figure, present the coefficients, T-statistics, and significant p-values for each relationship, providing empirical evidence on the crucial role of ethics in shaping public perceptions of AI and influencing behavior in interacting with this technology.

**Table 4.** Hypotheses testing results

| Hypotesis | Coefficient | T Statistics | p Values | Decision |
|---|---|---|---|---|
| **H1 :** Ethics AI Practices -> AI-Driven Societal Impact_ | 0.538 | 8.919 | 0.000 | Positive and Significant |
| **H2 :** Ethics AI Practices -> AI Behavioral Analysis | 0.534 | 9.534 | 0.000 | Positive and Significant |
| **H3 :** Ethical AI Practices -> AI Perception Dynamics -> AI-Driven Societal Impact | 0.220 | 3.827 | 0.000 | Positive and Significant |
| **H4 :** Ethical AI Practices -> AI Perception Dynamics -> AI Behavioral Analysis | 0.231 | 5.087 | 0.000 | Positive and Significant |
| **H5 :** AI Perception Dynamics -> AI-Driven Societal Impact_ | 0.327 | 4.042 | 0.000 | Positive and Significant |
| **H6 :** AI Perception Dynamics -> AI Behavioral Analysis | 0.342 | 5.676 | 0.000 | Positive and Significant |

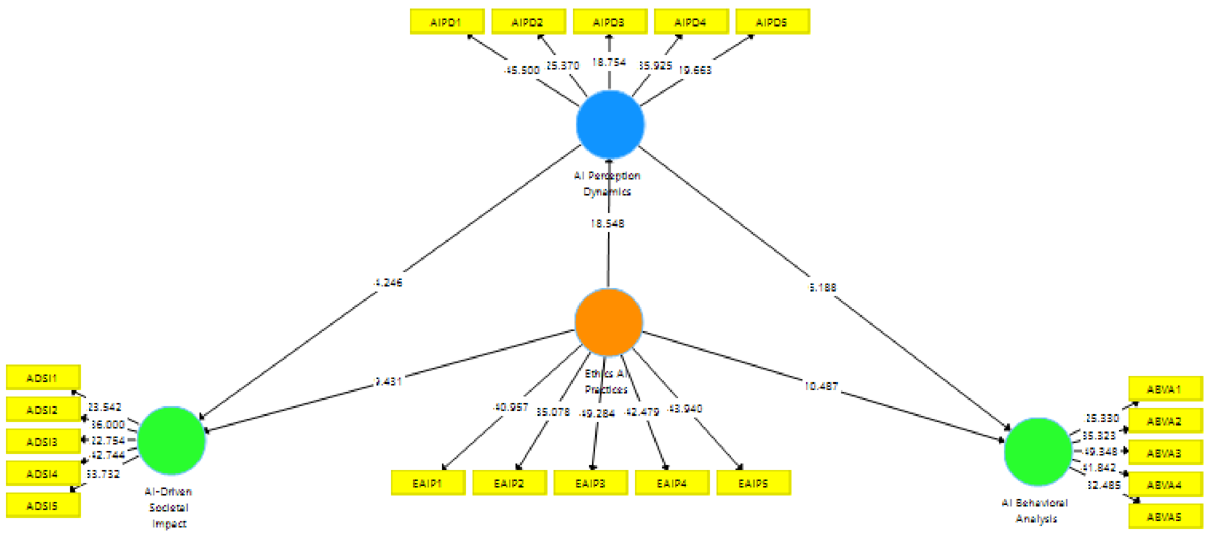


**Figure 3.** Structure model

To evaluate the proposed relationships within the conceptual model in figure 3, a structural model assessment was conducted using path coefficients, T-statistics, and significance values. Table 4 presents the results of hypothesis testing across six proposed pathways. All hypothesized relationships were found to be positive and statistically significant ($p < 0.001$), indicating strong empirical support for the structural model. The most prominent direct effects were observed from Ethics in AI Practices to both AI-Driven Societal Impact (H1) and AI Behavioral Analysis (H2), underscoring the pivotal role of ethical principles such as transparency, fairness, and accountability in shaping societal perceptions and behavioral responses to AI. Furthermore, the mediating role of AI Perception Dynamics in H3 and H4 confirms that public perception significantly enhances the impact of ethical AI practices on both societal outcomes and user behavior.

Additionally, the results demonstrate that AI Perception Dynamics significantly influence both AI-Driven Societal Impact (H5) and AI Behavioral Analysis (H6). These findings highlight the critical function of public perception in facilitating the acceptance and integration of AI technologies across various societal domains. The validated model reinforces the importance of embedding ethics into AI development not only for direct influence but also for indirectly shaping more favorable public attitudes and behaviors. Collectively, these findings emphasize that ethical AI practices—when aligned with positive public perceptions—can substantially foster trust, encourage responsible use, and enhance the societal value of AI systems.

### *3.4. Discussion*

In Hypotheses H1 and H2, the results reveal that Ethics in AI Practices has a strong direct influence on AI-Driven Societal Impact (coefficient 0.538, T-statistic 8.919) and AI Behavioral Analysis (coefficient 0.534, T-statistic 9.534), with significant p-values at the 0.001 level. These high coefficients confirm that ethical practices in AI implementation—such as transparency, accountability, and adherence to ethical standards—play an essential role in fostering positive public perceptions of AI's social impact and encouraging proactive and positive behavioral responses toward using AI technologies. This finding aligns with previous studies emphasizing that ethics in AI not only builds public trust but also shapes perceptions that AI serves not only a functional role but also holds a high degree of social responsibility (Kerstan et al., 2024; Regona et al., 2022).

Additionally, Hypothesis H3 reveals an indirect effect of Ethics in AI Practices on AI-Driven Societal Impact through the mediation of AI Perception Dynamics. With a coefficient of 0.220 and a T-statistic of 3.827, this hypothesis indicates that while ethical practices directly influence societal perceptions of AI's impact, positive perceptions mediated through AI Perception Dynamics enhance this impact. This means that good ethical practices can improve public perceptions of AI as a safe and beneficial technology, thereby strengthening AI's perceived social impact. Previous studies have shown that positive perceptions of AI, supported by ethical practices, can increase trust and public engagement, which is essential for widespread acceptance of the technology(Regona et al., 2022).

Hypothesis H4 elaborates on the mediating role of AI Perception Dynamics in the relationship between Ethics in AI Practices and AI Behavioral Analysis. With a coefficient of 0.231 and a T-statistic of 5.087, this finding suggests that positive public perceptions of AI, shaped by the application of ethical practices, can significantly encourage more active public engagement with AI. These positive perceptions, especially regarding AI's safety, fairness, and transparency, contribute to building a deeper trust in AI. This finding is consistent with the literature, which shows that perceptions of AI’s safety and ethicality are key determinants in fostering trust that drives active use and public participation in AI technologies (Oluwaseun Augustine Lottu et al., 2024; Tseng et al., 2021).

Furthermore, Hypotheses H5 and H6 demonstrate that AI Perception Dynamics has a significant direct impact on both AI-Driven Societal Impact (coefficient 0.327, T-statistic 4.042) and AI Behavioral Analysis (coefficient 0.342, T-statistic 5.676). These findings highlight that public perception of AI plays a central role in shaping how this technology is accepted and utilized in daily life. Positive perceptions of AI, especially concerning its safety and social benefits, reduce barriers to technology adoption, facilitating smoother integration of AI across sectors such as education, healthcare, and public administration. Previous studies indicate that positive perceptions of AI are instrumental in creating a supportive social environment, which ultimately reduces resistance to AI and facilitates the technology's broader adoption (Forbes, 2021; Lauer, 2021).

Overall, the structural model results presented in Table 4 and Figure 3 provide empirical evidence that Ethics in AI Practices has both direct and indirect effects on AI Perception Dynamics, AI-Driven Societal Impact, and AI Behavioral Analysis. These findings support modern theories on technology acceptance and AI ethics, emphasizing that applying ethical principles is essential for building public trust and fostering social acceptance of AI. This approach aligns with the responsible AI framework, where transparency, accountability, and adherence to ethical standards are foundational to achieving broader social benefits from AI technologies (Felländer et al., 2022; Oladoyinbo et al., 2024).

The findings of this study hold substantial implications for AI developers, policymakers, and organizations. The significant influence of ethical AI practices on perceptions and behaviors suggests that strategies prioritizing ethical considerations can enhance sustainable social acceptance of AI technologies. Recent literature underscores the importance of ethics in AI development, positing that ethical frameworks can shape public attitudes and acceptance substantially. For instance, Dwivedi (Dwivedi et al., 2021)assert that ethical AI practices not only increase user trust but also facilitate the adoption of AI across various sectors(Dwivedi et al., 2021).

Moreover, the critical role of AI perception dynamics in influencing social and individual responses highlights the need for public education and transparent communication by AI developers. Jungwirth and Haluza argue that fostering an understanding of AI's capabilities and limitations is essential to build public trust and acceptance (Jungwirth & Haluza, 2023). Through transparent communication and educational initiatives, developers can cultivate a more informed public that is supportive of AI adoption.

Policies that prioritize the development of fair, transparent, and ethical technology are expected to enhance public engagement and maximize the social benefits derived from AI. Recent studies advocate for comprehensive policy frameworks that address ethical concerns while promoting innovation. For example, Khonakdar emphasizes the importance of regulatory frameworks that ensure ethical AI practices in healthcare, which could serve as a model for other sectors (khonakdar, 2024). This discussion illustrates that an ethical approach to AI development is crucial for fostering positive public perceptions. By prioritizing ethics, enhancing public understanding, and promoting transparent communication, stakeholders can strengthen AI's social impact and encourage proactive, constructive engagement with AI technologies. Integrating ethical considerations into AI practices not only supports sustainable acceptance but also aligns AI with broader societal values, ultimately benefiting all involved stakeholders.

In this study, we explored the influence of ethical AI practices on AI-driven societal and behavioral impact, with a particular focus on the mediating role of AI Perception Dynamics. The PLS-SEM analysis provided insights into the direct, indirect, and total effects of ethical constructs such as transparency, accountability, and fairness on both public perceptions and behavioral responses. The findings highlight the essential role of these ethical practices in fostering trust, social acceptance, and responsible interaction with AI technologies. Ethical AI practices are a crucial foundation for shaping public perceptions and behavioral responses towards AI in various domains(Kumar Jaiswal et al., 2023). The strong relationship between ethical standards and societal impact confirms that when ethical principles are prioritized, AI technologies are more likely to gain public trust and acceptance. This trust further encourages users to engage with AI systems confidently and responsibly. Prior studies have similarly emphasized that transparent and fair AI implementations reduce skepticism and increase societal integration of AI applications(Kuleshov et al., 2020).

The mediating role of AI Perception Dynamics is also notable. Our findings reveal that ethical practices do not merely exert direct influence but also indirectly impact outcomes through shaping how people perceive AI (Yang & Lee, 2024). This aligns with previous literature suggesting that public perception, once positively shaped by ethics, enhances AI's perceived societal benefit and encourages constructive user behavior. Moreover, perceptions of safety, fairness, and transparency serve as psychological assurances for users, boosting their willingness to adopt and interact with AI systems (Valerio, 2024). Behavioral implications are clearly evident in this study. When the public perceives AI systems as ethically governed, they are more likely to demonstrate favorable behavioral responses, including increased engagement, cooperation, and proactive usage of AI technologies. This pattern supports the importance of embedding ethical values such as transparency, fairness, and accountability into AI system design (Benjamin Samson Ayinla et al., 2024; Fathahillah et al., 2023; Zhu, 2021). In line with our empirical results, where ethical AI practices had a significant positive effect on behavioral analysis (H2) and societal impact (H1), these findings reaffirm that when ethical principles are visibly applied, individuals not only trust AI more but also interact with it more positively and confidently.

Furthermore, our data show that AI Perception Dynamics significantly mediates the relationship between ethical practices and behavior (H4), a result echoed by global evidence that public trust is not only influenced by design but also by perception and value alignment (Galloway et al., 2020; Winfield & Jirotka, 2018). The behavioral shift is more pronounced when individuals perceive AI systems as inclusive, explainable, and designed with their values in mind. This perception creates a “feedback loop” where ethical design enhances perception, which in turn amplifies behavioral engagement. Additionally, co-production models that include community voices during AI development have proven effective in building legitimacy and reducing skepticism, particularly in underserved populations (Crockett et al., 2024). Our findings empirically validate these claims and highlight that prioritizing user values through ethical frameworks is essential for ensuring that AI adoption leads to positive societal transformation.

This research is further supported by a growing body of literature emphasizing that ethical design is not a peripheral concern, but rather a core driver of public trust, behavioral intention, and long-term acceptance of AI. Our findings particularly the mediating role of AI Perception Dynamics in the relationship between ethical practices and behavioral outcomes (H4) align with broader evidence showing that ethical awareness influences how individuals perceive fairness and transparency in AI interactions (Contreras & Jaimes, 2024; Fakhri, Ahmar, et al., 2024; Mahande et al., 2025). This is especially important in educational and public-facing AI systems, where perceptions of bias or opacity can severely erode user engagement and institutional credibility (Fakhri, Putra, et al., 2024; Ruslan et al., 2024; Sharma & Ojha, 2021). Moreover, ethical frameworks that actively include transparency, fairness, and accountability have been shown to reduce skepticism and enhance both social and behavioral responses to AI in real-world settings.

The implications of this study are multifaceted, spanning both theoretical advancement and practical application. Scientifically, the research contributes to existing frameworks by empirically validating the mediating role of public perception in the relationship between ethical AI practices and both societal and behavioral outcomes. These findings demonstrate that ethics in AI particularly transparency, fairness, accountability, and explainability are not merely abstract ideals, but measurable drivers of user trust and engagement. When these ethical principles are embedded throughout the AI lifecycle, they create a feedback loop in which improved perception enhances user behavior, resulting in broader societal impact.

Practically, the study provides actionable insights for three primary stakeholders: developers, policymakers, and educators. For AI developers, ethical design must be prioritized not only to meet performance expectations but also to foster legitimacy and trust, particularly in sensitive domains such as healthcare and finance. Policymakers must move beyond technical compliance to establish regulatory frameworks that make ethical quality visible and enforceable through transparency and inclusion mechanisms. Meanwhile, educational institutions are encouraged to integrate AI ethics into curricula, ensuring future professionals are equipped with both technological proficiency and ethical awareness. Together, these implications call for a collaborative, cross-sectoral approach to responsible AI, where ethical practices are institutionalized across design, governance, and education to enable trustworthy and socially aligned innovation.

Future research should extend the current model by incorporating broader sociocultural and psychological mediators that may influence the pathway from ethical AI design to behavioral and societal outcomes. Variables such as digital literacy, civic trust, and cultural norms are likely to moderate how individuals interpret and respond to ethical AI practices, especially across diverse demographic or institutional settings. Comparative studies across sectors such as healthcare, education, and finance could offer deeper insights into how ethical perceptions and impacts differ depending on context and risk sensitivity (Benjamin Samson Ayinla et al., 2024; Muhammad Hani Bayan, 2024). In addition, intervention-based studies that implement real-time features such as algorithm explainability, fairness notifications, or bias transparency tools may help evaluate whether enhanced user awareness fosters greater public trust and engagement with AI systems (Ruttkamp-Bloem, 2020).

Furthermore, future research should explore the long-term effects of ethical literacy, particularly when embedded within multidisciplinary educational curricula. Investigating how ethical training influences users' ability to critically evaluate and responsibly interact with AI can inform strategies for building a more informed and empowered public. This approach may also contribute to the cultivation of future developers and decision-makers who are not only technically capable, but also ethically attuned in designing and deploying AI technologies aligned with societal values.

## 4. Conclusion

The findings of this study provide clear answers to the proposed research questions. First, ethical AI practices, particularly transparency, fairness, and accountability, were shown to have a significant positive effect on public perception of AI, indicating that ethical alignment is crucial for building societal trust. Second, these ethical practices also directly influenced both AI-driven societal impact and user behavior, confirming that ethical design enhances both engagement and public value. Finally, the study empirically demonstrated that AI perception plays a mediating role in linking ethics to behavior and societal outcomes, reinforcing the idea that how people perceive AI ethics critically shapes their responses to the technology. Overall, these insights affirm the importance of embedding ethical principles in AI systems to foster public acceptance, responsible behavior, and inclusive technological advancement.

Despite these contributions, this study is subject to several limitations that should be acknowledged. The use of purposive sampling focusing on participants with prior knowledge of AI may constrain the generalizability of the findings to the broader public, particularly to those with limited exposure to AI technologies. Furthermore, the cross-sectional design limits the ability to capture dynamic changes in perception and behavior over time, making it difficult to establish causal inferences. To address these gaps, future research should consider longitudinal or experimental designs, as well as more diverse sampling across demographic, cultural, and sectoral contexts. Doing so would offer a more comprehensive understanding of how ethical AI practices interact with public perception and behavior in varying real-world scenarios.

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