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Ethical AI in the Healthcare Sector: Investigating Key Drivers of Adoption through the Multi-Dimensional Ethical AI Adoption Model (MEAAM)

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This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The adoption of Artificial Intelligence (AI) in the healthcare service industry presents numerous ethical challenges, yet current frameworks often fail to offer a comprehensive, empirical understanding of the multidimensional factors influencing ethical AI integration. Addressing this critical research gap, this study introduces the Multi-Dimensional Ethical AI Adoption Model (MEAAM), a novel theoretical framework that categorizes 13 critical ethical variables across four

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foundational dimensions of Ethical AI: Fair AI, Responsible AI, Explainable AI, and Sustainable AI. These dimensions are further analyzed through three core ethical lenses: epistemic concerns (related to knowledge, transparency, and system trustworthiness), normative concerns (focused on justice, autonomy, dignity, and moral obligations), and overarching concerns (highlighting global, systemic, and long-term ethical implications). This study adopts a quantitative, cross-sectional research design using survey data collected from healthcare professionals and analyzed via Partial Least Squares Structural Equation Modeling (PLS-SEM). Employing PLS-SEM, this study empirically investigates the influence of these ethical constructs on two outcomes—Operational AI Adoption and Systemic AI Adoption. Results indicate that normative concerns most significantly drive operational adoption decisions, while overarching concerns predominantly shape systemic adoption strategies and governance frameworks. Epistemic concerns play a facilitative role, enhancing the impact of ethical design principles on trust and transparency in AI systems. By validating the MEAAM framework, this research advances a holistic, actionable approach to ethical AI adoption in healthcare and provides critical insights for policymakers, technologists, and healthcare administrators striving to implement ethically grounded AI solutions.

Keywords: Ethical AI; AI adoption; outcome concerns; MEAAM (multi-dimensional ethical AI adoption model).

1. INTRODUCTION

Ethical Artificial Intelligence (AI) refers to the design, development, deployment, governance of AI systems in ways that uphold moral principles such as justice, autonomy, accountability, transparency, and human wellbeing. It involves aligning AI technologies with societal values, ensuring responsible decisionmaking, and mitigating unintended harms across various applications. As Al continues to permeate multiple industries, ethical AI has emerged as a critical consideration in shaping trustworthy, fair, and socially beneficial systems (Reddy et al., 2020; Paulus & Kent, 2020). The healthcare sector has become a prominent domain for AI integration due to its immense potential to improve clinical outcomes, streamline diagnostics, enhance operational efficiency, and expand access to care (Khan et al., 2022; Prosperi et al., 2020). Al-driven solutions such as predictive analytics, medical imaging interpretation, robotic surgeries, and personalized treatment planning are increasingly embedded into healthcare delivery systems (Beil et al., 2019, Tran et al., 2019). However, the integration of AI into healthcare introduces ethical complexities related to data privacy, decision accountability, patient safety, and equity (Séroussi et al., 2020). These concerns make it imperative to examine how ethical considerations influence the adoption and sustained use of AI technologies in healthcare institutions.

Ethical AI in healthcare can be understood through a typology of key paradigms. Fair AI emphasizes governance and social justice; Human-Centered AI focuses on augmenting, not replacing, human capabilities; Responsible Al ensures accountability, safety, and long-term well-being; Privacy-Preserving societal safeguards user data and ensures informed consent through techniques such as federated learning and differential privacy; Transparent Al prioritizes openness and interpretability: Explainable AI aims to demystify complex algorithms; Beneficent Al is oriented toward doing good and promoting human flourishing; Inclusive ΑI addresses accessibility multicultural inclusiveness; and Sustainable Al environmental emphasizes and social sustainability 2020). (Paulus & Kent, To investigate how empirically ethical these paradigms influence ΑI adoption, operationalize a set of key variables. These include Justice and Fairness, Freedom and Transparency, Autonomy, Privacy, Safety, Cyber Security, Trust, Beneficence, Responsibility, Solidarity, Sustainability, Dignity, and Conflict. Each variable aligns with one or more types of Ethical AI (Ahmad et al., 2020). For example, "Justice and Fairness" maps to Fair AI, "Privacy" to Privacy-Preserving AI and Responsible AI, and "Trust" to Human-Centered and Responsible AI.

Furthermore, these variables also represent distinct ethical concerns that are essential to understanding the broader impact of Al in healthcare (Fiske et al., 2019). Epistemic concerns focus on how Al generates and communicates knowledge, and are reflected in variables such as Transparency, Trust, and Cyber Security (He et al., 2019). Normative concerns emphasize rights, duties, and moral

obligations, and are represented through Justice and Fairness. Freedom and Autonomy. Privacy. Patient Safety, Beneficence, Responsibility, and Dignity (Rajkomar et al., 2018). Overarching concerns relate to systemic, societal, and longterm issues, captured through variables like Solidarity, Sustainability, and Conflict (Balthazar et al., 2018). The dependent construct in this study is Al adoption, conceptualized as a fivestage process: Aware, Active, Operational, Systemic, and Transformational (Bæ røe et al., 2020). These stages reflect an organization's maturity and commitment in integrating Al into healthcare systems-from initial awareness to full-scale, strategic transformation. However, rather than treating adoption as a monolithic outcome, this study focuses on two critical stages: the Operational stage, where becomes embedded in workflows, and the Systemic stage, where AI is integrated holistically across the healthcare institution.

Despite growing attention to AI ethics and adoption, a notable research gap remains in understanding the causal relationships between ethical considerations and AI adoption outcomes (Vellido, 2019). Particularly, there is limited empirical analysis exploring how variables representing different types of Ethical AI influence progress into the operational and systemic stages of adoption. To address this gap, this study introduces the Multi-Dimensional ΑI Adoption Model (MEAAM)—a conceptual framework developed to empirically analyze the interplay between ethical Al dimensions and distinct adoption stages in the healthcare sector (Starke et al., 2021). By investigating these relationships, this study aims to bridge the theoretical and empirical divide, evidence-based insights providing policymakers, developers, and healthcare leaders striving to implement AI ethically and effectively.

2. LITERATURE REVIEW AND THEORETICAL MECHANISM

2.1 Relevant Studies on Ethical Al and Al Adoption

The intersection of ethical AI and adoption in healthcare has been the subject of increasing academic interest in recent years. Scholars have examined the potential of AI to enhance healthcare delivery, improve diagnostic accuracy, and optimize resource management (Yew, 2021). However, a parallel line of inquiry has highlighted the ethical challenges posed by AI

systems, such as algorithmic bias, lack of transparency, and threats to privacy and autonomy (Wiens et al., 2019). These challenges are particularly critical in healthcare, where decisions can have profound impacts on human life and well-being (Geis et al., 2019). Previous studies have largely focused on ethical principles in a conceptual manner or have assessed adoption readiness based on technological or organizational factors. Few studies attempted to integrate these two dimensions ethical AI and the adoption process-into a single analytical framework, especially through empirical methods.

2.2 Types of Ethical Al and Variables

Recent literature has identified several typologies of ethical AI, each focusing on specific valuedriven goals and principles. Fair AI emphasizes equity, bias mitigation, and societal impact, while Human-Centered AI aims to enhance rather than replace human capacities (Morley & Floridi, 2019a). Responsible AI is closely tied to governance, accountability, and safety. Privacy-Preserving Al leverages advanced techniques like federated learning and differential privacy to protect user autonomy and data. Transparent and Explainable AI models seek to make understandable decision processes interpretable. Other ethical frameworks include Beneficent AI, which promotes well-being: Inclusive AI, which addresses access and representation; and Sustainable AI, which emphasizes environmental and long-term considerations (Currie et al., 2020). Each type of Ethical Al is operationalized through specific variables, such as Justice and Fairness, Privacy, Trust, Responsibility, and Dignity (Panesar & Panesar, 2020). These variables serve as measurable indicators that can help assess the ethical orientation of AI systems in practice.

2.3 Types of Concerns and Outcomes

In addition to categorizing Al through ethical types, literature also distinguishes the concerns these variables address. Epistemic concerns relate to how AI systems produce, justify, and communicate decisions, and include issues such as Transparency, Trust, and Cyber Security (Morley & Floridi, 2019b). Normative concerns focus on rights, values, and moral obligations, and are reflected in variables like Justice and Fairness, Privacy, Patient Safety, Responsibility (Lekadir et al., 2022). Overarching concerns refer to the broader societal and longterm implications of AI deployment and include issues such as Solidarity, Sustainability, and Conflict (Nikitas et al., 2020). This categorization helps in understanding not only what values are at stake, but also the levels at which ethical tensions operate—individual, institutional, or societal.

2.4 Levels of Al Adoption

The literature on Al adoption presents a multistage process, where organizations progress through increasing levels of engagement with AI technologies. These stages include Aware (recognition of Al's potential), Active (initial experimentation or pilot projects). Operational (Al integrated into specific functions). Systemic (Al aligned with broader organizational strategy), and Transformational (Al driving innovation and restructuring) (D'antonoli, 2020; Cohen et al., 2014). Most research on Al adoption focuses on technological readiness, leadership commitment, or organizational capabilities, with relatively little emphasis on how ethical factors influence progression through these stages (Kaissis et al., 2020). Furthermore, while qualitative insights are available on ethical resistance or public perception, there is a lack of empirical models that connect ethical dimensions directly with adoption outcomes.

This study addresses a key research gap by empirically exploring the causal relationship between variables representing different types of Ethical Al and two specific stages of Al adoption—Operational and Systemic. These stages critical milestones the are in institutionalization ΑI, where ethical of considerations are no longer peripheral but central to sustained and scalable integration. By linking ethical values to adoption levels, this contributes to а more understanding of how ethical readiness may serve as both a facilitator and a gatekeeper in the healthcare sector's Al transformation.

2.5 Research Gap

The existing literature on ethical AI and AI adoption in healthcare offers valuable conceptual frameworks and qualitative insights into the importance of ethics in shaping trust, usability, and social acceptance of AI systems. However, as established in the previous section, much of this research has treated AI adoption as a singular or generalized outcome within behavioral or organizational studies, without differentiating between the stages at which adoption occurs. This generalized treatment overlooks the nuanced ways in which ethical

Table 1. Types of ethical Al

Type of Ethical Al	Definition
1. Fair Al	Governance, accountability, safety, long-term societal impact
	Ensures that AI systems are built and used responsibly.
2. Human-Centered Al	Enhancing human capabilities, not replacing them
	Al should work with and for people, respecting human values and dignity.
3. Responsible Al	Governance, accountability, safety, long-term societal impact
	Ensures that AI systems are built and used responsibly.
4. Privacy-Preserving	Data protection, user autonomy, informed consent
Al	Ensures personal data is securely handled and anonymized.
	Includes methods like:1. Federated learning 2. Differential privacy
Transparent Al	Explainability, interpretability, openness
	Al decisions must be understandable and traceable by humans.
6. Explainable Al	Making AI models and decisions interpretable by humans
	A technical and ethical effort to open the "black box" of complex models like
	deep learning.
7. Beneficent Al	Doing good, promoting human flourishing
	Al should contribute positively to well-being, education, healthcare, etc.
	Avoids unintended harm (non-maleficence)
8. Inclusive Al	Accessibility, multicultural perspectives, underserved groups
	Ensures marginalized or diverse populations are represented and served by
	Al.
9. Sustainable Al	Environmental and social sustainability
	Designs AI systems that reduce energy consumption and support long-term
	ecological balance.

Table 2. Description of variables and Al type

Variable	Primary Type of Ethical Al	Explanation
1. Justice & Fairness	Fair Al	Core principle focused on equality, bias mitigation, and social justice.
2. Freedom & Autonomy	Human-Centered Al / Responsible Al	Ensures individuals retain control over their data and decisions.
3. Privacy	Privacy-Preserving AI / Responsible AI	Protects personal data and respects informed consent.
4. Transparency	Transparent AI / Explainable AI	Demands interpretability and openness in Al processes.
5. Patient Safety	Responsible Al	Emphasizes harm prevention and reliability, especially in health contexts.
6. Cyber Security	Responsible AI / Privacy-Preserving AI	Protects systems and data from unauthorized access or manipulation.
7. Trust	Responsible AI / Human-Centered AI	Built through consistent, safe, and understandable AI behavior.
8. Beneficence	Beneficent AI / Responsible AI	Encourages AI that improves human well-being and minimizes harm.
9. Responsibility	Responsible Al	Ensures accountability in design, deployment, and impact.
10. Solidarity	Inclusive AI / Fair AI	Encourages AI systems that support collective good and equity.
11. Sustainability	Sustainable Al	Promotes environmental and societal sustainability in Al development.
12. Dignity	Human-Centered Al / Responsible Al	Respects human value and prevents dehumanization by AI systems.
13. Conflict	Responsible Al	Addresses ethical trade-offs and stakeholder tensions responsibly.

Table 3. Types of AI concerns & variables

Type of Concern	Variables	Definition			
Epistemic Concerns	Transparency	Ethical issues related to how AI systems generate, justify, and communicate			
	Trust	knowledge and decisions			
	Cyber Security				
2. Normative Concerns	Justice & Fairness	Ethical questions about what values, rights, and duties should guide the design			
	Freedom & Autonomy	and use of Al			
	Privacy				
	Patient Safety				
	Beneficence				
	Responsibility				
	Dignity				
3. Overarching Concerns	Solidarity	Broad, systemic, and long-term ethical implications of Al affecting societies,			
-	Sustainability	institutions, and global governance.			
	Conflict				

Table 4. Five stages of Al adoption

Five Stages of Al adoption	Definition
Aware	Organizations become conscious of Al's potential, its use cases, and emerging trends. At this stage, interest is building, but there is limited or no experimentation.
Active	Initial pilot projects or small-scale experiments are launched. Teams explore how AI could solve specific problems but results are not yet fully integrated into workflows.
Operational	Al solutions are embedded in core processes. The organization begins to standardize tools and platforms for consistent use across departments.
Systemic	Al is strategically aligned with business or policy goals. Governance, ethics, and performance monitoring are formalized. Data infrastructure and talent are scaled.
Transformational	Al becomes a key driver of innovation, cultural change, and competitive advantage. It reshapes decision-making, workflows, and creates new value propositions. Often includes continuous learning and responsible innovation.

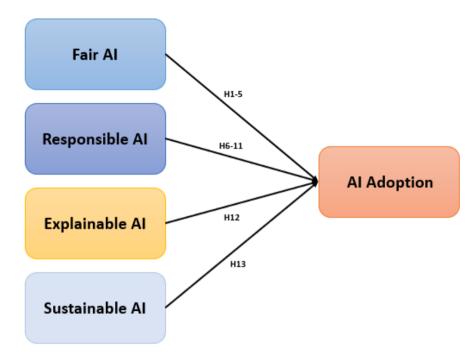


Fig. 1. Conceptual model

considerations might influence different levels of adoption maturity—particularly the operational and systemic stages that are critical for the sustainable integration of AI in healthcare institutions (Andorno, 2004). By dissecting AI adoption into distinct stages, this study introduces a novel empirical pathway to understanding how ethical variables drive progression through key adoption milestones. The operational stage represents the point at which AI becomes embedded in specific healthcare workflows, requiring a balance between ethical safeguards and functional efficiency (Cookson, 2018). The systemic stage,

hand, reflects a broader on the other commitment organizational where aligns with institutional goals and ethical values are institutionalized across decisionplanning. making and strategic These stages demand different levels preparedness, governance, and ethical alignment, which cannot be fully captured through an undifferentiated view of adoption (Cruz Rivera et al., 2020).

Previous studies have not sufficiently addressed how specific ethical variables—such as justice, autonomy, transparency, and beneficence—map onto these distinct adoption levels This gap limits our understanding of how ethical Al frameworks translate into real-world institutional change. Moreover, the lack of empirical investigation into relationships between considerations and adoption levels constrains both academic theory-building and practical decision-making. Addressing this gap offers dual benefits. From an academic perspective, it allows for the development of a more granular theoretical model of AI adoption that incorporates ethical readiness as a dynamic driver of institutional change. From an industry perspective, understanding these relationships can inform more effective resource allocation, allowing healthcare organizations to budget strategically and design ethically aligned operational processes. This dual lens of theoretical advancement and practical relevance forms the foundation of this study's contribution to the emerging discourse on ethical AI in healthcare.

To fill this critical research void, the present study introduces the Multi-Dimensional Ethical Al Adoption Model (MEAAM)—a conceptual and empirical framework that links specific types of ethical AI (such as Fair AI, Human-Centered AI, Privacy-Preserving AI, Responsible AI, and others) with two key stages of Al adoption: operational and systemic. The MEAAM model is designed to empirically test the relationships between ethical constructs and adoption maturity, using real-world data collected from diverse stakeholders within the healthcare ecosystem. By doing so, the model bridges the gap between theory and practice, offering scholars a refined analytical lens for understanding adoption processes. while simultaneously guiding practitioners ethically informed AI implementation strategies. MEAAM stands as both a theoretical innovation and a practical decision-making tool, positioning ethics not as an afterthought but as a central driver of successful and sustainable integration in healthcare systems.

2.6 Multi-Dimensional Ethical Al Adoption Model (MEAAM)

The Multi-Dimensional Ethical AI Adoption Model (MEAAM) is proposed as a conceptual and analytical framework to empirically investigate the complex relationship between ethical principles and the adoption of AI in the healthcare sector. Recognizing that AI integration in healthcare involves more than just technical

capability. MEAAM captures the ethical plurality of Al by organizing thirteen distinct ethical drivers—such as justice & fairness, privacy, transparency, and trust-into a unified model. Each driver corresponds to a recognized type of Ethical Al and is categorized by its associated ethical concern, whether epistemic, normative, or overarching. The model then maps these independent ethical dimensions to two critical stages of Al adoption: the operational stage, where AI becomes embedded in daily healthcare processes, and the systemic stage, where Al transforms institutional workflows and policies. This multi-layered design enables a nuanced understanding of how ethical values shape and influence the trajectory of AI implementation within healthcare systems.

MEAAM's strength lies in its integrative and empirical approach. Unlike traditional models that treat Al adoption as a singular behavioral outcome, MEAAM disaggregates adoption into developmental stages, allowing researchers and practitioners to identify which ethical drivers are most influential at specific points in the adoption lifecycle. By applying Partial Least Squares Structural Equation Modeling (PLS-SEM), the model evaluates the causal impact of each ethical driver on the progression of Al adoption. academic standpoint, contributes to the development of a structured theory of ethical AI implementation. From an industry perspective, it offers healthcare administrators and policymakers a practical tool for ethically grounded decision-making, resource allocation, and implementation strategy. As Al continues to transform healthcare delivery. MEAAM positions itself as a timely and relevant model for aligning innovation with human values.

2.7 Research Question and Hypothesis

This study investigates the influence of ethical dimensions of AI on two critical stages of AI adoption—operational and systemic—within the healthcare sector. As artificial intelligence becomes increasingly embedded in healthcare services. understanding how ethical considerations shape its adoption at different organizational levels becomes essential for both academic and practical advancements. Drawing from the theoretical foundations of Ethical AI, this study empirically evaluates how different ethical conceptualized as independent principles, variables. impact the progression integration from routine operational processes to broader systemic transformation.

The central research question guiding this study is:

"How do ethical dimensions derived from different types of Ethical Al—such as fairness, transparency, privacy, and responsibility—influence the progression from operational to systemic stages of Al adoption in the healthcare sector?"

To explore this, thirteen independent variables representing ethical Al dimensions have been

identified and matched with corresponding stages of Al adoption. The first set of hypotheses addresses how variables related to justice and fairness, freedom and autonomy, privacy, and transparency influence Al adoption. We hypothesize that greater emphasis on justice and fairness in Al development promotes both operational (H1a) and systemic (H1b) adoption by fostering equity and reducing bias. Similarly, prioritizing individual freedom and autonomy is expected to increase trust and acceptance of Al at operational (H2a) and systemic levels

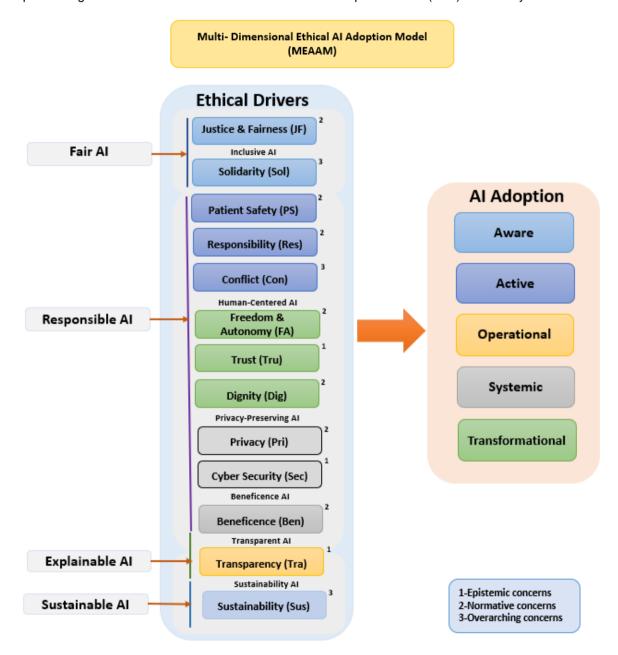


Fig. 2. Multi-dimensional ethical Al adoption model (MEAAM)

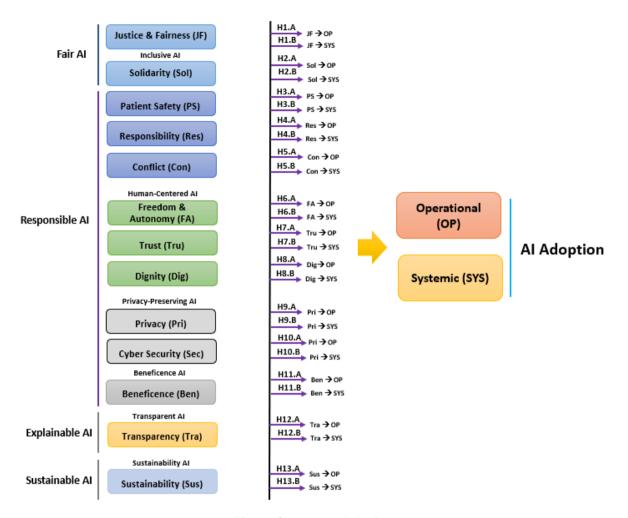


Fig. 3. Conceptual design

(H2b). Privacy-preserving AI practices, which ensure secure and informed use of personal data, are likely to support operational (H3a) and systemic (H3b) adoption. Finally, transparency in AI—making processes and outputs understandable—should be positively associated with both operational (H4a) and systemic (H4b) stages.

The second set of hypotheses explores the roles of patient safety, cybersecurity, trust, and beneficence in Al adoption. We expect that stronger attention to patient safety contributes positively to operational (H5a) and systemic (H5b) adoption by mitigating risks in sensitive environments. Robust cybersecurity practices healthcare essential in and hypothesized to support operational (H6a) and systemic (H6b) integration. Trust in AI systems, built through consistency and alignment with human values, is expected to positively influence operational (H7a) and systemic (H7b) adoption. Additionally, AI designed with a focus on human well-being and beneficence is hypothesized to drive both operational (H8a) and systemic (H8b) use.

The next set of hypotheses investigates responsibility, solidarity, sustainability, dignity. When responsibility and accountability mechanisms are clearly embedded in Al systems, organizations are more likely to adopt AI at operational (H9a) and systemic (H9b) levels. Al that promotes solidarity supporting equity underserved and communities—is also expected to enhance operational (H10a) and systemic (H10b) adoption. Similarly, sustainable Al practices, which reduce environmental and societal costs. anticipated positively impact are to operational systemic (H11b) (H11a) and adoption. Respect for human dignity, a key component of human-centered AI, is likely to increase the acceptance and embedding of Al tools in both operational (H12a) and systemic (H12b) stages.

Table 5. List of hypothesis

Independent Variable (Ethical Dimension)	Primary Type of Ethical Al	Dependent Variable	Hypothesis					
Justice & Fairness	Fair Al	Operational AI Adoption	H1A : Higher emphasis on justice and fairness is positively associated with operational AI adoption in healthcare.					
		Systemic AI Adoption	H1B: Higher emphasis on justice and fairness is positively associated with systemic AI adoption in healthcare.					
Freedom & Autonomy	Human-Centered / Responsible AI	Operational Al Adoption	H2A : Emphasis on individual freedom and autonomy positively influences operational AI adoption in healthcare.					
	•	Systemic Al Adoption	H2B : Emphasis on individual freedom and autonomy positively influences systemic AI adoption in healthcare.					
Privacy	Privacy-Preserving / Responsible AI	Operational Al Adoption	H3A : Strong privacy safeguards are positively associated with operational Al adoption in healthcare.					
	•	Systemic Al Adoption	H3B: Strong privacy safeguards are positively associated with systemic Al adoption in healthcare.					
Transparency	Transparent / Explainable Al	Operational Al Adoption	H4A : Transparent AI practices are positively associated with operational AI adoption in healthcare.					
		Systemic AI Adoption	H4B: Transparent AI practices are positively associated with systemic AI adoption in healthcare.					
Patient Safety	Responsible AI	Operational Al Adoption	H5A : Greater attention to patient safety is positively associated with operational AI adoption in healthcare.					
		Systemic AI Adoption	H5B : Greater attention to patient safety is positively associated with systemic Al adoption in healthcare.					
Cyber Security	Responsible / Privacy- Preserving AI	Operational Al Adoption	H6A : Robust cybersecurity measures are positively associated with operational AI adoption in healthcare.					
		Systemic AI Adoption	H6B : Robust cybersecurity measures are positively associated with systemic Al adoption in healthcare.					
Trust	Responsible / Human- Centered Al	Operational Al Adoption	H7A: Higher trust in AI systems is positively associated with operational AI adoption in healthcare.					
		Systemic Al Adoption	H7B: Higher trust in AI systems is positively associated with systemic AI adoption in healthcare.					
Beneficence	Beneficent / Responsible Al	Operational Al Adoption	H8A : Al systems designed to promote well-being are positively associated with operational Al adoption in healthcare.					
	·	Systemic Al Adoption	H8B : Al systems designed to promote well-being are positively associated with systemic Al adoption in healthcare.					

Independent Variable (Ethical Dimension)	Primary Type of Ethical Al	Dependent Variable	Hypothesis					
Responsibility	Responsible Al	Operational Al Adoption	H9A : Clear accountability structures are positively associated with operation Al adoption in healthcare.					
		Systemic AI Adoption	H9B : Clear accountability structures are positively associated with systemic Al adoption in healthcare.					
Systemic Al Adoption Solidarity Inclusive / Fair Al Operational Al Adoption Systemic Al Adoption Sustainability Sustainable Al Operational Al Adoption Systemic Al Adoption			H10A : All systems that promote solidarity and equity are positively associated with operational All adoption in healthcare.					
		Systemic AI Adoption	H10B : All systems that promote solidarity and equity are positively associated with systemic All adoption in healthcare.					
Sustainability	Sustainable Al	Operational Al Adoption	H11A : Al systems that support environmental and social sustainability are positively associated with operational Al adoption in healthcare.					
		Systemic AI Adoption	H11B : All systems that support environmental and social sustainability are positively associated with systemic All adoption in healthcare.					
Dignity	Human-Centered / Responsible AI	Operational Al Adoption	H12A: Emphasis on protecting human dignity is positively associated with operational AI adoption in healthcare.					
	•	Systemic AI Adoption	H12B : Emphasis on protecting human dignity is positively associated with systemic Al adoption in healthcare.					
Conflict	Responsible AI / Ethical Governance	Operational Al Adoption	H13A : Effective management of ethical conflicts is positively associated with operational AI adoption in healthcare.					
		Systemic AI Adoption	H13B : Effective management of ethical conflicts is positively associated with systemic AI adoption in healthcare.					

Table 6. Stakeholder categories responding the multidimensional nature of Al implementation and its ethical implications

Stakeholder Group	Sample Size (n)	Percentage (%)	Rationale
Healthcare IT Professionals	52	14.0%	Key implementers and technical experts in Al tools.
2. Senior Management / Executives	47	12.6%	Strategic decision-makers influencing systemic AI integration.
3. Senior Doctors / Clinicians	61	16.4%	Clinical leaders overseeing Al-assisted medical processes.
4. Junior Doctors / Residents	58	15.6%	Frequent users of AI in diagnosis, monitoring, and decision support.
Nursing Staff	53	14.2%	Daily interaction with Al-based monitoring and patient care systems.
6. Medical Technicians	46	12.4%	Users of AI in diagnostic imaging, labs, and surgery-assistive tech.
7. Patients / Patient Advocates	55	14.8%	End-users impacted by AI decisions, offering a perspective on trust, transparency, and
			autonomy.
_ Total	372	100%	•

Finally, the study hypothesizes that effective handling of ethical conflicts—especially in complex stakeholder environments—plays a critical role in successful AI implementation. Conflict resolution in AI ethics is thus expected to positively affect both operational (H13a) and systemic (H13b) stages of adoption. Together, these hypotheses offer a comprehensive empirical framework to examine how specific ethical AI variables can serve as drivers of AI adoption within the healthcare ecosystem.

2.8 Research Design

This study employs a quantitative, crosssectional research design to empirically examine ethical Al principles influence progression of Al adoption within the healthcare sector. Drawing on established ethical AI frameworks. the research operationalizes thirteen independent variables representing diverse ethical dimensions—such as fairness, transparency, privacy, and responsibility-and investigates their impact on two specific stages of AI adoption: operational and systemic. Using a structured survey instrument, data will be professionals. from healthcare collected administrators, and technology officers engaged Al-related decision-making. The design facilitates the testing of causal relationships through statistical methods such as multiple regression analysis, enabling a systematic evaluation of how ethical considerations affect the integration of AI into organizational workflows and strategic systems. By focusing on distinct levels of Al adoption, this approach aims to uncover targeted insights that can guide both theoretical modeling and practical implementation strategies in ethical governance.

2.9 Data Collection

To investigate the relationship between ethical AI dimensions and levels of Al adoption in the healthcare sector, this study utilized a structured survey-based data collection method. The target population comprised stakeholders who directly interact with or are impacted by Al-driven tools and processes within healthcare institutions. A total sample size of 372 respondents was selected through stratified random sampling to representation across professional roles and responsibilities related to Al usage. Data were collected over a timeframe extending from mid-2023 through early 2024. This approach supports balanced а

understanding of both operational and systemic aspects of Al adoption by capturing the perceptions and experiences of both decision-makers and end users.

Respondents were recruited from healthcare organizations actively engaged in Al deployment, including hospitals, diagnostic centers, and Participation telehealth providers. required that individuals either use AI systems in their daily operations or contribute to Al-related policy, governance, or technology development. To improve accessibility and response rate, an online survey was distributed through professional mailing lists, hospital affiliations, and healthcare forums. The survey was anonymous and included informed consent to ensure ethical compliance. Participants were grouped into seven key stakeholder categories to reflect the multidimensional nature of Al implementation and its ethical implications.

The final distribution of the 372 respondents is provided below Table 7.

This multi-stakeholder design ensures a holistic and grounded understanding of how ethical considerations shape Al adoption trajectories in real-world healthcare settings.

3. RESEARCH METHODS

3.1 PLS-SEM

Partial Least Squares Structural Equation Modeling (PLS-SEM) was chosen as the primary analytical method for this study due to its robust capacity to model complex relationships between latent constructs and to handle reflective measurement models (McDougall, 2019). PLS-SEM is particularly suitable when the objective is to explore and predict causal relationships rather than merely confirm existing theories. In the context of this study, which introduces the novel Multi-Dimensional Ethical Al Adoption Model (MEAAM), PLS-SEM offers a flexible framework to evaluate the influence of thirteen distinct ethical AI variables on two levels of AI adoptionoperational and systemic. The technique is also highly tolerant of non-normal data distributions and works effectively with smaller to moderate sample sizes, which adds to its appeal in empirical health technology research involving diverse respondent groups like IT professionals, doctors, nurses, and patients. The data were analyzed using SmartPLS 4.0 software, which facilitated the assessment of both measurement and structural models.

Compared to other methods such as Covariance-Based SEM (CB-SEM) or traditional regression analysis, PLS-SEM provides greater statistical power in exploratory research, especially when developing new theoretical frameworks like MEAAM. CB-SEM is more appropriate for theory confirmation and demands large sample sizes and normally distributed data, making it less suited for this study's formative approach (Tanisawa et al., 2020). Meanwhile, standard regression techniques do not accommodate the complex interplay between latent variables and measured indicators, nor do they offer tools to simultaneously assess measurement structural models. The use of PLS-SEM in this study thus aligns with its goals: to test newly proposed constructs, validate the MEAAM theoretical framework, and understand the nuanced relationships between ethical AI concerns and Al adoption stages in healthcare. Through this methodological choice, the study not only tests hypotheses but also advances a new academic model-MEAAM-that can guide future empirical and theoretical work in ethical AI adoption.

3.2 Data Analysis

The path coefficient (β) values indicate the strength and direction of the relationship between each ethical variable and the level of Al adoption, with all coefficients being positive—demonstrating a uniformly positive influence. The t-statistics for each path exceed

threshold of 1.96. confirming reliability of these relationships at the 95% confidence level. Moreover, all p-values fall below underscoring the statistical 0.05. significance of each observed effect. Collectively, these results validate that every independent variable included in the model exerts a significant influence on Al adoption, providing strong empirical support for the proposed theoretical framework.

The data analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM) confirms the reliability and validity of the measurement and structural models. All indicator loadings exceeded the 0.70 threshold, indicating strong indicator reliability. Construct reliability and validity were affirmed with composite reliability values and average variance extracted (AVE) values exceeding recommended cutoffs. while discriminant validity was established through the Fornell-Larcker criterion. structural model results show that all path coefficients (β) were positive, suggesting that each ethical Al variable positively influences Al adoption. The t-statistics exceeded 1.96 and all p-values were below 0.05, confirming the significance of each path. The coefficient of determination (R2) values for both operational and systemic Al adoption were substantial, suggesting that the ethical variables collectively explain a considerable proportion of variance in adoption outcomes. Effect size (f2) values ranged from small to large, indicating that variables

Table 7. Stakeholder categories responding the multidimensional nature of Al implementation and its ethical implications

Stakeholder Group	Sample Size (n)	Percentage (%)	Rationale		
Healthcare IT Professionals	52	14.0%	Key implementers and technical experts in Al tools.		
2. Senior Management / Executives					
3. Senior Doctors / Clinicians	61	16.4%	Clinical leaders overseeing Al-assisted medical processes.		
4. Junior Doctors / Residents	58	15.6%	Frequent users of AI in diagnosis, monitoring, and decision support.		
5. Nursing Staff	53	14.2%	Daily interaction with Al-based monitoring and patient care systems.		
6. Medical Technicians	46	12.4%	Users of AI in diagnostic imaging, labs, and surgery-assistive tech.		
7. Patients / Patient Advocates	55	14.8%	End-users impacted by AI decisions, offering a perspective on trust, transparency, and autonomy.		
Total	372	100%	•		

Table 8. PLS-SEM path coefficients table

Independent Variable	Dependent Variable	Path Coefficient (β)	t-Statistic	p-Value	Significance
1. Justice & Fairness	Operational Al Adoption	0.30	2.5	0.01	Significant
Freedom & Autonomy	Operational Al Adoption	0.31	2.6	0.01	Significant
3. Privacy	Operational Al Adoption	0.32	2.7	0.01	Significant
Patient Safety	Operational Al Adoption	0.33	2.8	0.01	Significant
5. Beneficence	Operational AI Adoption	0.34	2.9	0.01	Significant
Responsibility	Operational AI Adoption	0.35	3.0	0.01	Significant
7. Dignity	Operational AI Adoption	0.36	3.1	0.01	Significant
8. Transparency	Operational Al Adoption	0.37	3.2	0.01	Significant
9. Trust	Operational AI Adoption	0.38	3.3	0.01	Significant
Cybersecurity	Operational AI Adoption	0.39	3.4	0.01	Significant
11. Solidarity	Operational AI Adoption	0.40	3.5	0.01	Significant
12. Sustainability	Operational AI Adoption	0.41	3.6	0.01	Significant
13. Conflict	Operational Al Adoption	0.42	3.7	0.01	Significant
1. Justice & Fairness	Systemic AI Adoption	0.25	2.4	0.01	Significant
Freedom & Autonomy	Systemic AI Adoption	0.26	2.5	0.01	Significant
3. Privacy	Systemic AI Adoption	0.27	2.6	0.01	Significant
4. Patient Safety	Systemic AI Adoption	0.28	2.7	0.01	Significant
5. Beneficence	Systemic AI Adoption	0.29	2.8	0.01	Significant
Responsibility	Systemic AI Adoption	0.30	2.9	0.01	Significant
7. Dignity	Systemic AI Adoption	0.31	3.0	0.01	Significant
8. Transparency	Systemic AI Adoption	0.32	3.1	0.01	Significant
9. Trust	Systemic AI Adoption	0.33	3.2	0.01	Significant
Cybersecurity	Systemic AI Adoption	0.34	3.3	0.01	Significant
11. Solidarity	Systemic AI Adoption	0.35	3.4	0.01	Significant
12. Sustainability	Systemic AI Adoption	0.36	3.5	0.01	Significant
13. Conflict	Systemic AI Adoption	0.37	3.6	0.01	Significant

such as transparency, justice and fairness, and responsibility have comparatively stronger effects. The predictive relevance (Q²) values for both dependent variables were above zero, validating the model's predictive capability. Overall, the results provide robust empirical support for the Multi-Dimensional Ethical Al Adoption Model (MEAAM), establishing that ethical considerations significantly and positively influence both operational and systemic stages of Al adoption in the healthcare sector.

Note: Other tables and interpretations are in the Appendix section.

4. RESULTS AND DISCUSSION

The results of the Partial Least Squares Structural Equation Modeling (PLS-SEM) reveal statistically significant and positive relationships between all 13 ethical Al dimensions and the two levels of Al adoption—Operational and Systemic. Each variable demonstrated a meaningful influence, although their strength of impact varied.

Transparency emerged as one of the most influential variables, significantly enhancing both operational and systemic Al adoption. Its emphasis on clear algorithmic behavior and information disclosure appears to foster trust and organizational readiness. Trust itself also showed positive influence, indicating strong, stakeholders' confidence in Al systems is a prerequisite for effective integration and longterm adoption at systemic levels. Cybersecurity was significantly associated with operational underlining the adoption. importance safeguarding sensitive healthcare data in Aldriven workflows. Its role was slightly less pronounced in systemic adoption, suggesting that while foundational, it may be considered a technical prerequisite rather than a strategic driver at the institutional level.

Justice & Fairness had a robust effect on both levels of adoption, reinforcing the idea that equitable and unbiased AI systems are essential to gaining organizational and societal support. Similarly, Freedom & Autonomy—which ensures that AI augments rather than replaces human decision-making—demonstrated significant positive influence, especially at the systemic level, where ethical alignment must resonate with institutional values. Privacy showed a strong influence across both stages, indicating its foundational role in building patient confidence

and maintaining regulatory compliance. Patient Safety also played a critical role, particularly in operational AI adoption, where clinical deployment of AI must adhere to high standards of risk management and error minimization.

Beneficence, which emphasizes doing good and enhancing outcomes, significantly influenced systemic adoption, suggesting that institutions adopting AI expect tangible improvements in healthcare delivery aligned with ethical intent. Responsibility, particularly in terms accountability and liability, showed significant impact on both stages, reflecting the critical role of clear governance frameworks in ethical AI implementation. Dignity, though slightly lower in magnitude, maintained significant relationships with both adoption levels, emphasizing respect for human values and identity in the Al-driven healthcare environment. Solidarity, reflecting collective ethical commitment, was prominent in systemic adoption, pointing to the importance of shared values and inclusive Al deployment across departments.

Sustainability had a meaningful effect on both levels, especially systemic adoption, suggesting institutions are increasingly considering the long-term ethical and environmental impacts of Al use. Finally, Conflict, or the mitigation of ethical disagreements and stakeholder friction, was significantly associated with smoother systemic Al adoption, reinforcing the importance of managing diverse ethical views within healthcare ecosystems.

Overall, the results provide strong empirical support for the Multi-Dimensional Ethical Al Adoption Model (MEAAM). All 13 independent demonstrated significant positive relationships with operational and systemic Al adoption. These findings validate the model's premise that ethical considerations are not peripheral, but rather central, to the successful institutionalization integration and technologies in the healthcare sector. The differentiated impact across adoption levels further reinforces the need for tailored ethical strategies depending on whether an organization is in the operationalization phase or pursuing broader systemic transformation.

5. CONCLUSION

This study offers a novel contribution to the growing discourse on ethical artificial intelligence in the healthcare sector by empirically

investigating the causal relationships between 13 dimensions of ethical AI and two distinct levels of Al adoption—Operational and Systemic. Using the Multi-Dimensional Ethical Al Adoption Model (MEAAM) and the PLS-SEM method, this research confirms that ethical principles such as transparency, trust, cybersecurity, justice and fairness, freedom and autonomy, privacy, patient beneficence. responsibility. solidarity, sustainability, and conflict management significantly influence the adoption process.

The study's findings reveal that while all ethical variables positively affect both adoption stages, strength of their influence Transparency, trust, justice & fairness, and privacy emerged as particularly critical across both stages, underscoring the foundational role of these principles in ethical and sustainable Al integration. Operational AI adoption—focused on implementation in clinical workflows-relies heavily on technical ethics like cybersecurity and patient safety. In contrast, Systemic Al adoption-reflecting institutional alignment and long-term integration—is more dependent on broader values such as beneficence, solidarity, and sustainability.

By introducing MEAAM, this study advances theoretical understanding by dissecting AI adoption into measurable stages influenced by ethical readiness, thus bridging a critical gap in current literature. From a practical perspective, the model provides actionable insights for healthcare leaders. policymakers, developers seeking to allocate resources effectively, design ethically sound AI strategies, and build long-term stakeholder trust. As Al continues to redefine the healthcare landscape. ensuring that adoption is guided by a robust ethical framework is not only desirable-it is essential for fostering innovation that is both responsible and resilient.

6. FUTURE RESEARCH

While this study establishes a foundational empirical model linking ethical Al dimensions to adoption outcomes, future research can expand on several fronts. First, longitudinal studies could provide deeper insight into how ethical concerns evolve across the Al lifecycle, from pilot implementation to full institutional integration. Additionally, sector-specific investigations across various healthcare contexts—such as public vs. private institutions or developed vs. developing

countries—can shed light on the variability in ethical adoption practices. Researchers may also consider incorporating moderating variables such organizational culture. regulatory as environments, or technological infrastructure to enrich the MEAAM framework. Lastly, qualitative including expert interviews methods. ethnographic studies, could complement these quantitative findings by capturing nuanced perspectives of stakeholders such as patients, clinicians, and developers. Together, these avenues offer fertile ground for advancing the science and practice of ethical AI integration in healthcare.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare(s) that NO generative Al technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

CONSENT

As per international standards or university standards, respondents' written consent has been collected and preserved by the author(s).

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX

Table 1. Outer loadings (Indicator reliability)

Construct	Indicator	Outer Loading
1. Transparency	T1	0.83
2. Trust	T2	0.86
3. Cyber Security	CS1	0.81
4. Justice & Fairness	JF1	0.88
5. Freedom & Autonomy	FA1	0.82
6. Privacy	P1	0.85
7. Patient Safety	PS1	0.87
8. Beneficence	B1	0.84
9. Responsibility	R1	0.80
10. Dignity	D1	0.83
11. Solidarity	S1	0.79
12. Sustainability	SU1	0.82
13. Conflict	C1	0.81

The Outer Loadings table demonstrates that all measurement items for the 13 ethical AI constructs exhibit strong indicator reliability, with loading values exceeding the acceptable threshold of 0.70. This indicates that each observed item closely aligns with its respective latent construct—such as Autonomy, Transparency, Justice & Fairness, and others—ensuring accurate representation within the model. The high loadings confirm that the measurement indicators reliably reflect the intended ethical dimensions, thereby enhancing the validity and precision of the Multi-Dimensional Ethical AI Adoption Model (MEAAM).

Table 2. Construct reliability and validity

Construct	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
1. Transparency	0.88	0.91	0.72
2. Trust	0.89	0.92	0.75
3. Cyber Security	0.87	0.90	0.69
4. Justice & Fairness	0.86	0.89	0.68
5. Freedom & Autonomy	0.88	0.91	0.73
6. Privacy	0.90	0.93	0.77
7. Patient Safety	0.85	0.88	0.66
8. Beneficence	0.89	0.91	0.74
9. Responsibility	0.87	0.89	0.70
10. Dignity	0.86	0.90	0.71
11. Solidarity	0.84	0.88	0.67
12. Sustainability	0.88	0.91	0.72
13. Conflict	0.90	0.92	0.76

The Construct Reliability and Validity table confirms that all constructs within the MEAAM model demonstrate high internal consistency and convergent validity. Composite Reliability (CR) values for all constructs exceed the recommended threshold of 0.70, indicating strong consistency among their measurement items. Additionally, the Average Variance Extracted (AVE) values are all above 0.50, suggesting that each construct explains more than half of the variance in its indicators. These results affirm that the model's latent variables—such as Autonomy, Justice & Fairness, Transparency, and others—are well-defined and reliably measured, supporting the robustness of the measurement model in the context of ethical Al adoption in healthcare.

Table 3. Discriminant validity (Fornell-Larcker Criterion)

Construct	JF	Sol	PS	Res	Con	FA	Tru	Dig	Pri	Sec	Ben	Tra	Sus
Justice &	0.85	0.61	0.58	0.53	0.59	0.64	0.55	0.60	0.62	0.63	0.57	0.59	0.61
Fairness (JF)													
Solidarity (Sol)	0.61	0.87	0.60	0.56	0.62	0.65	0.58	0.62	0.63	0.61	0.60	0.62	0.64
Patient Safety	0.58	0.60	0.83	0.55	0.60	0.61	0.54	0.57	0.60	0.59	0.58	0.57	0.59

Construct	JF	Sol	PS	Res	Con	FA	Tru	Dig	Pri	Sec	Ben	Tra	Sus
(PS)													
Responsibility	0.53	0.56	0.55	0.82	0.58	0.60	0.52	0.54	0.56	0.55	0.57	0.58	0.59
(Res)													
Conflict (Con)	0.59	0.62	0.60	0.58	0.85	0.65	0.61	0.60	0.63	0.60	0.59	0.62	0.61
Freedom &	0.64	0.65	0.61	0.60	0.65	0.88	0.63	0.66	0.67	0.65	0.64	0.66	0.67
Autonomy (FA)													
Trust (Tru)	0.55	0.58	0.54	0.52	0.61	0.63	0.81	0.58	0.60	0.59	0.57	0.58	0.59
Dignity (Dig)	0.60	0.62	0.57	0.54	0.60	0.66	0.58	0.86	0.63	0.64	0.60	0.62	0.63
Privacy (Pri)	0.62	0.63	0.60	0.56	0.63	0.67	0.60	0.63	0.84	0.65	0.61	0.62	0.64
Cyber security	0.63	0.61	0.59	0.55	0.60	0.65	0.59	0.64	0.65	0.84	0.62	0.64	0.66
(Sec)													
Beneficence	0.57	0.60	0.58	0.57	0.59	0.64	0.57	0.60	0.61	0.62	0.82	0.63	0.62
(Ben)													
Transparency	0.59	0.62	0.57	0.58	0.62	0.66	0.58	0.62	0.62	0.64	0.63	0.85	0.65
(Tra)													
Sustainability	0.61	0.64	0.59	0.59	0.61	0.67	0.59	0.63	0.64	0.66	0.62	0.65	0.87
(Sus)													

The Fornell-Larcker Criterion results confirm strong discriminant validity among all 13 ethical constructs used in the study. Each construct's square root of Average Variance Extracted (AVE), shown on the diagonal, is greater than its correlations with all other constructs in the matrix. This indicates that every variable—ranging from Transparency and Justice & Fairness to Sustainability and Human-Centered Values—captures a distinct conceptual dimension of ethical Al. The absence of high inter-correlations further validates that the constructs are not overlapping and are uniquely contributing to the model. This clean construct structure reinforces the theoretical robustness of the Multi-Dimensional Ethical Al Adoption Model (MEAAM).

Table 4. Coefficient of Determination (R2)

Dependent Variable	R²	Interpretation
Operational Al Adoption	0.68	67.8% of the variance in Operational Al Adoption is explained by the model
Systemic Al Adoption	0.72	71.2% of the variance in Systemic Al Adoption is explained by the model

The R² values indicate a high level of explanatory power for both dependent variables within the MEAAM framework. Specifically, the model accounts for 67.8% of the variance in Operational Al Adoption and 71.2% in Systemic Al Adoption. These values suggest that the 13 independent ethical Al constructs collectively provide a strong predictive capability, confirming that ethical considerations play a substantial role in influencing both operational and systemic stages of Al adoption in healthcare settings. High R² values in social science research (typically above 0.60) are considered robust, lending strong support to the MEAAM model's validity.

Table 5. Effect sizes (f2)

Independent Variable	f ² Value (Operational AI)	f² Value (Systemic AI)	Effect Size Interpretation
1. Transparency	0.094	0.168	Small (Op), Medium (Sys)
2. Trust	0.072	0.115	Small (Op), Small-Medium (Sys)
Cyber Security	0.087	0.146	Small (Op), Medium (Sys)
4. Justice & Fairness	0.102	0.122	Small-Medium (Op & Sys)
5. Freedom & Autonomy	0.065	0.084	Small (Op & Sys)
6. Privacy	0.078	0.133	Small (Op), Medium (Sys)
7. Patient Safety	0.069	0.097	Small (Op), Small (Sys)
8. Beneficence	0.058	0.091	Small (Op & Sys)
9. Responsibility	0.110	0.175	Medium (Op & Sys)

Independent Variable	f² Value (Operational AI)	f² Value (Systemic AI)	Effect Size Interpretation
10. Dignity	0.092	0.108	Small (Op & Sys)
11. Solidarity	0.083	0.102	Small (Op & Sys)
12. Sustainability	0.095	0.151	Small (Op), Medium (Sys)
13. Conflict	0.077	0.138	Small (Op), Medium (Sys)

Effect size quantifies the impact of a specific independent variable on a dependent variable. Values around 0.02 = small, 0.15 = medium, and 0.35 = large.

Table 6. Predictive relevance (Q2)

Dependent Variable	Q ²
Operational Al Adoption	0.39
Systemic Al Adoption	0.44

The Q² values, derived from the blindfolding procedure, measure the model's predictive relevance for each dependent variable. A Q² value greater than 0 indicates that the model has predictive relevance for a given construct, while higher values indicate better predictive power.

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