Approval Page

Integrating AI-Driven Clinical Decision Support Systems to Improve Diagnostic Accuracy and Treatment Planning in Healthcare

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Abstract

The purpose of this quantitative, correlational study was to examine the extent to which perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity predicted healthcare professionals' intention to use artificial intelligence–driven Clinical Decision Support Systems (AI-CDSS) to improve diagnostic accuracy and treatment planning. Guided by an integrated framework combining the Technology Acceptance Model (TAM) and Diffusion of Innovation theory, this study investigated how these perceptions influenced behavioral intention to use AI-CDSS. Data were collected through an online survey administered to licensed healthcare professionals. Of the 152 individuals who accessed the survey, 109 responses met inclusion criteria and were retained for analysis, resulting in a usable response rate of 71.7%. Multiple linear regression analysis showed that the overall model was statistically significant, $F(5, 103) = 19.55$, $p < .001$, explaining 48.7% of the variance in intention to use AI-CDSS ($R^2 = .487$, adjusted $R^2 = .462$). Relative advantage emerged as the strongest significant predictor, followed by complexity, whereas perceived ease of use, perceived usefulness, and compatibility were not statistically significant in the full model. Findings indicate that clinicians' adoption intentions are influenced more by comparative value and manageable implementation burden than by usability or workflow alignment alone. Practical implications include emphasizing meaningful clinical advantage while reducing perceived complexity. Future research should examine trust, organizational readiness, and perceived risk using longitudinal and intervention-based designs.

Dedication

This dissertation is dedicated to my family, whose unwavering love, encouragement, and belief in me sustained my determination throughout this journey. To my mother, wife, and children, whose futures inspire me to model perseverance and purpose. And to all who pursue knowledge to improve the lives of others—may this work contribute in some way to meaningful progress in healthcare and society.

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Special thanks to the healthcare professionals and IT specialists who participated in this study. Their willingness to share their experiences and insights was essential for the completion of this research. Without their cooperation, this study would not have been possible.

I am also grateful to my colleagues, friends, and family for their emotional support and encouragement during this journey. Their understanding and patience provided me with the strength to overcome challenges and stay focused on my goals.

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To all who have played a part in this journey, I am deeply appreciative of your contributions and support. Thank you for helping make this research possible.

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Chapter 1: Introduction

The integration of artificial intelligence (AI)–driven Clinical Decision Support Systems (CDSS) into healthcare practice held significant potential for improving patient outcomes, enhancing diagnostic accuracy, and enabling more effective treatment planning. AI-powered CDSS were designed to analyze large volumes of patient data and generate evidence-based recommendations that supported clinicians in making more informed decisions, ultimately reducing human error (Liu et al., 2021). Despite these advantages, healthcare professionals have encountered substantial barriers when adopting and integrating AI-driven CDSS into clinical practice. These barriers have included technical limitations, organizational resistance, and individual perceptions about the reliability and effectiveness of AI technologies in clinical decision-making (Ng & Koo, 2020). Understanding these challenges is critical because successful adoption of AI technologies in healthcare depends on how healthcare professionals perceived their usefulness, ease of use, and compatibility with existing workflows (Venkatesh & Davis, 2020). This study focused on these factors—specifically perceived ease of use (PEOU), perceived usefulness (PU), relative advantage, compatibility, and complexity—and how these variables influenced the adoption of AI-driven CDSS in clinical settings.

The relevance of this research is significant, as it contributes to the broader goal of enhancing healthcare delivery through AI. Despite notable advancements in AI technologies, the adoption of AI-driven CDSS has remained limited in many healthcare settings (Venkatesh & Bala, 2020). Research has suggested that one of the primary reasons for low adoption rates is the perception of barriers such as complexity, concerns about integration with existing workflows, and healthcare professionals' resistance to change (Liu et al., 2021). Understanding these barriers and facilitators is essential for improving the implementation of CDSS and advancing

technology-acceptance theories in healthcare (Fetters et al., 2020). While considerable research has explored general technology adoption, a gap remains in studies specifically examining factors that have influenced the adoption of AI-driven technologies in clinical environments (Ng & Koo, 2020). This research addressed that gap by examining the key predictors associated with the acceptance and integration of AI-driven CDSS in healthcare.

The technology acceptance model (TAM) and diffusion of innovation (DOI) theory served as the theoretical foundations for this study (Davis, 1989; Rogers, 2003). Both models emphasize the importance of perceived usefulness and ease of use in determining technology adoption (Davis, 1989). However, additional research was needed to investigate how these factors operated in complex clinical environments with high levels of responsibility and interconnected workflows (Venkatesh & Davis, 2020). This study built on existing literature by examining additional factors, such as compatibility and complexity, which had not been fully explored in the context of AI-driven CDSS (Venkatesh & Bala, 2020).

This study was warranted because, despite the technological promise of AI-driven CDSS, their potential remained underutilized due to persistent resistance to adoption in healthcare settings (Liu et al., 2021). By identifying and analyzing the factors influencing healthcare professionals' decisions to adopt AI technologies, this research provided actionable insights for healthcare leaders and policymakers. These insights informed strategies to overcome barriers to AI adoption, ultimately supporting improvements in clinical decision-making and patient care (Moser & Kalton, 2020).

The integration of AI in healthcare accelerated rapidly between 2020 and 2025, driven by advancements in machine learning, predictive analytics, and digitized medical records. AI-CDSS tools were developed to assist clinicians by providing diagnostic suggestions, risk assessments,

alerts, and treatment recommendations based on large datasets and clinical guidelines. Although the technology showed promise, empirical evidence has revealed varying levels of acceptance among clinicians. Prior research has indicated that clinicians' perceptions—particularly regarding usefulness, ease of use, workflow alignment, trust, and complexity—played a crucial role in adoption decisions.

The TAM and the DOI are widely used frameworks for understanding technology adoption in healthcare environments. TAM emphasizes perceived usefulness and perceived ease of use, whereas DOI highlights innovation attributes such as relative advantage, compatibility, and complexity. Integrating these models offers a comprehensive perspective for evaluating clinician adoption of AI-CDSS.

Statement of the Problem

The problem addressed in this study was the difficulty healthcare professionals faced in integrating AI-driven CDSS into clinical practice within large hospitals in the United States, despite the demonstrated potential of these technologies to enhance diagnostic accuracy, treatment planning, and patient outcomes. Although AI-driven technologies have been shown to improve decision-making processes, reduce diagnostic errors, and enhance patient care (Venkatesh & Davis, 2020), large hospitals have continued to face significant barriers in their widespread adoption and effective implementation. These barriers include organizational resistance, technological challenges, and individual perceptions regarding the reliability and utility of AI systems (Liu, Li, & Zhao, 2021).

Although large hospitals generally possessed more resources and technological infrastructure compared to smaller clinics or rural healthcare settings, they still encountered difficulties in adopting advanced technologies such as AI-driven CDSS (Ng & Koo, 2020).

Despite having the capacity to lead in AI adoption, these institutions continued to experience inconsistent implementation. The complexity of AI systems, concerns about their compatibility with existing workflows, and resistance from healthcare professionals remained major obstacles to successful adoption (Rogers, 2003).

Failure to address these challenges limited the potential system-wide benefits of AI in healthcare, hindering improvements in clinical decision-making and patient care. This problem affected healthcare professionals, organizations, and ultimately patients, as the full potential of AI-driven systems remained untapped (Liu et al., 2021). This study explored how perceived ease of use (PEOU), perceived usefulness (PU), relative advantage, compatibility, and complexity influenced AI adoption in large hospitals, identifying key barriers and facilitators to successful integration (Venkatesh & Davis, 2020).

Purpose of the Study

The purpose of this quantitative, cross-sectional survey methodology study was to examine the key factors that influenced the adoption of AI–driven CDSS in healthcare settings. This study specifically focused on how PEOU, PU, relative advantage, compatibility, and complexity affected healthcare professionals' intentions and decisions to integrate these systems into routine clinical practice. Understanding these dynamics was critical because the adoption of AI-driven CDSS had the potential to transform healthcare by improving diagnostic accuracy, treatment planning, and patient outcomes, yet adoption rates remained lower than expected.

This study employed a structured survey instrument designed to capture healthcare professionals' perceptions of the identified constructs. Likert-scale items, adapted from validated measures grounded in the TAM and the DOI theory, were developed to assess participants' attitudes toward AI-driven CDSS. These survey items measured the extent to which PEOU, PU,

relative advantage, compatibility, and complexity influenced adoption decisions (Venkatesh & Davis, 2020; Rogers, 2003). To ensure accuracy and credibility, the instrument was adapted from previously validated scales and underwent structured expert review to strengthen clarity, relevance, and alignment with the study constructs.

The study targeted healthcare professionals, including physicians, nurses, and IT specialists, working in clinical settings where CDSS adoption was either under consideration or already partially implemented. These participants represented individuals who interacted directly with CDSS or whose roles were impacted by the integration of such systems. An a priori power analysis was conducted using G*Power 3.1.9.7 to estimate the minimum sample size required to detect meaningful effects in the planned regression analyses. The final analytic sample consisted of 109 retained participants, which exceeded the minimum required sample size and provided adequate statistical power for the study. This sample size ensured sufficient statistical power for regression and correlation analyses, which allowed the testing of hypotheses regarding relationships among study variables (Moser & Kalton, 2020).

Data were collected through an online survey administered to participants in urban and suburban healthcare environments, where institutions were more likely to integrate AI technologies. To protect confidentiality and encourage honest responses, pseudonyms were assigned, and no identifying information was disclosed. The findings provided valuable insights into the extent to which TAM and DOI constructs predicted adoption behaviors, thereby offering practical guidance to healthcare administrators, policymakers, and system developers seeking to enhance AI integration in clinical practice.

Introduction to Framework

This study was guided by an integrated theoretical framework that combined the TAM (Davis, 1989) and the DOI theory (Rogers, 2003). Together, these frameworks provided a comprehensive foundation for understanding how both individual perceptions and organizational factors shaped the adoption of AI–driven CDSS in healthcare environments.

TAM, originally introduced by Davis (1989), focuses on the individual-level determinants of technology acceptance. It identifies two key constructs: PEOU and PU. PEOU refers to the degree to which healthcare professionals believe that AI-driven CDSS are free of effort to operate, while PU captures the extent to which these professionals perceive that CDSS improves their job performance, such as enhancing diagnostic accuracy or treatment planning. In healthcare, where clinicians have faced complex workflows and high accountability, these two constructs are particularly critical in shaping behavioral intention to adopt emerging technologies. TAM has demonstrated its ability to predict technology acceptance across multiple domains, making it an essential model for this study (Venkatesh & Davis, 2020).

While TAM explains individual attitudes toward adoption, DOI extends the analysis to organizational and systemic levels. Rogers (2003) emphasized that innovations spread within social systems through attributes such as relative advantage, compatibility, and complexity. Relative advantage assesses the degree to which CDSS are perceived as superior to traditional decision-making processes. Compatibility evaluates the alignment of CDSS with existing clinical workflows, institutional practices, and professional values. Complexity represents the perceived difficulty of learning, implementing, and using CDSS within a healthcare setting. Together, these constructs highlight the systemic facilitators and barriers that healthcare institutions and professionals encounter during adoption (Ng & Koo, 2020).

Integrating TAM and DOI strengthened this study by ensuring that both micro-level and macro-level perspectives were considered. By unifying these models, the study captured the cognitive evaluations of clinicians (PEOU and PU) and reflected the organizational realities of healthcare systems (relative advantage, compatibility, and complexity). This integrated framework also supported the development of the study's research questions, hypotheses, and methodological design, ensuring consistency across conceptual and operational levels.

Ultimately, this dual-theory approach enhanced the explanatory power of the study and ensured that the findings contributed to both theoretical advancement in technology adoption research and practical strategies for overcoming barriers to AI-CDSS integration in healthcare.

Introduction to Research Methodology and Design

This study employed a quantitative, cross-sectional research design to investigate the factors influencing the adoption of AI-CDSS in healthcare. A quantitative approach was appropriate because it allowed for the systematic measurement and statistical examination of relationships among clearly defined variables. The cross-sectional design captured participants' perceptions at a single point in time, providing an efficient means of examining adoption-related factors without requiring longitudinal data collection (Creswell, 2014). This design aligned with the study's purpose of examining measurable relationships among constructs derived from the TAM and DOI theory.

Data were collected through an online survey administered to healthcare professionals, including physicians, nurses, and health information technology specialists who had used or been exposed to AI-CDSS in clinical environments. The survey instrument consisted of Likert-type items adapted from previously validated TAM and DOI instruments (Davis, 1989; Rogers, 2003). These items measured PEOU, PU, relative advantage, compatibility, complexity, and

intention to use AI-CDSS. Each construct was operationalized using multiple items to capture the multidimensional nature of technology adoption perceptions. To support content clarity and usability, the survey instrument was reviewed by subject-matter experts, and minor revisions were made to improve item wording, structure, and alignment with clinical terminology prior to full deployment.

The sampling strategy involved purposive sampling of approximately 74 participants, as determined through an a priori power analysis conducted using G*Power 3.1.9.7. This calculation ensured sufficient statistical power to detect meaningful relationships in correlation and multiple regression analyses at a 95% confidence level with an alpha level of .05 (Moser & Kalton, 2020). Participants were recruited from urban and suburban healthcare settings where AI-enabled clinical technologies were more likely to be implemented, enhancing the relevance of the data to real-world clinical contexts.

Collected data were analyzed using both descriptive and inferential statistical techniques. Descriptive statistics were used to summarize participant characteristics and central tendencies of study variables. Inferential analyses, including Pearson correlation and multiple regression, were conducted to examine the strength, direction, and predictive relationships between the independent variables (PEOU, PU, relative advantage, compatibility, and complexity) and the dependent variable (intention to use AI-CDSS). These analyses were used to address the research question and evaluate the study hypotheses.

By employing this methodological approach, the study generated empirical evidence regarding factors that influence healthcare professionals' intentions to adopt AI-CDSS. The selected design ensured analytical rigor and methodological transparency while supporting the

study's broader objective of advancing theoretical understanding and informing AI-CDSS implementation strategies in healthcare settings.

Research Questions

RQ1

To what extent did perceived ease of use (PEOU) and perceived usefulness (PU) influence the adoption of AI-driven Clinical Decision Support Systems (CDSS) in healthcare settings?

RQ2

To what extent did the relative advantage of AI-driven Clinical Decision Support Systems (CDSS) influence healthcare professionals' intention to use the technology?

RQ3

To what extent did compatibility and complexity influence the integration of AI-driven Clinical Decision Support Systems (CDSS) into healthcare workflows?

Hypotheses

Based on the research questions, the following testable hypotheses were proposed. These hypotheses aligned directly with the problem and purpose statements, utilizing the same constructs (PEOU, PU, relative advantage, compatibility, and complexity), population (healthcare professionals including physicians, nurses, and IT specialists), and setting (general urban or suburban healthcare environments).

$H1_0$

There was no significant relationship between perceived ease of use (PEOU), perceived usefulness (PU), and the adoption of AI-driven Clinical Decision Support Systems (CDSS) in healthcare settings.

$H1_a$

Perceived ease of use (PEOU) and perceived usefulness (PU) had a positive and significant influence on the adoption of AI-driven Clinical Decision Support Systems (CDSS) in healthcare settings.

- *Independent variables:* PEOU and PU
- *Dependent variable:* Adoption of CDSS

$H2_0$

There was no significant relationship between the perceived relative advantage of AI-driven CDSS and healthcare professionals' intention to use the technology.

$H2_a$

The relative advantage of AI-driven CDSS had a positive and significant influence on healthcare professionals' intention to use the technology.

- *Independent variable:* Relative advantage
- *Dependent variable:* Intention to use AI-CDSS

$H3_0$

There was no significant relationship between compatibility, complexity, and the integration of AI-driven Clinical Decision Support Systems (CDSS) into healthcare workflows.

$H3_a$

Compatibility positively influenced the integration of AI-driven CDSS into healthcare workflows, while complexity negatively affected the integration process.

- *Independent variable 1:* Compatibility (expected to have a **positive** relationship with integration)

- *Independent variable 2:* Complexity (expected to have a **negative** relationship with integration)
- *Dependent variable:* Integration of CDSS into workflows

These hypotheses were testable through a quantitative research design using survey data collected from healthcare professionals exposed to AI-CDSS. All variables, population, and setting remained consistent with the study's purpose and problem statement, ensuring alignment and feasibility. This framework supported the identification of barriers and facilitators to adoption and provided practical insights for successful AI integration in clinical practice.

Significance of the Study

The significance of this study lay in its direct examination of one of the most pressing issues in modern healthcare: the adoption and integration of AI–driven CDSS. Although these systems hold substantial promise for improving diagnostic accuracy, enhancing treatment planning, and reducing human error, adoption rates in clinical practice remains limited. Understanding the barriers and facilitators of adoption was therefore essential for realizing the transformative potential of AI in healthcare.

At the theoretical level, this study contributes to the TAM and the DOI theory by extending their application to AI-driven CDSS in large healthcare organizations. TAM highlights individual-level constructs such as PEOU and PU, whereas DOI expands the framework by incorporating systemic constructs such as relative advantage, compatibility, and complexity. By integrating these models, the study provided a holistic understanding of adoption that encompassed both individual clinician perceptions and broader organizational contexts. This contribution advanced scholarship in technology adoption research by testing a dual-theory

framework in a high-stakes healthcare domain in which patient outcomes depended on decision-making accuracy (Liu et al., 2021; Venkatesh & Davis, 2020).

At the practical level, the study offers actionable insights for healthcare professionals, administrators, and policymakers. The findings identified the factors that most strongly predicted adoption and those that most significantly inhibited integration. For healthcare leaders, this information can inform strategies to support clinicians through training, workflow alignment, and system optimization. For policymakers, the results provide evidence-based guidance for developing supportive policies and incentives that encourage responsible AI integration into healthcare delivery. For technology developers, the study highlights design features and system attributes that most influenced acceptance, ensuring that future CDSS tools would align with user needs and organizational realities.

At the societal level, the study underscores the broader importance of AI adoption for improving healthcare quality, reducing diagnostic errors, and promoting efficiency. As healthcare systems face increasing pressures associated with population growth and rising patient complexity, the integration of AI technologies represents a critical avenue for sustaining high-quality patient care. By examining the adoption process, the study contributes to maximizing the societal benefits of AI while minimizing the risks associated with underutilization.

Overall, the significance of this research extends across theoretical, practical, and societal dimensions. The study can enrich academic literature on technology adoption, guide healthcare leaders in overcoming barriers to AI integration, and contribute to public health outcomes by supporting the effective use of innovative clinical decision-support technologies.

Definitions of Key Terms

Adoption

Adoption refers to the decision by healthcare professionals to begin using a new technology or system in their clinical practice. In the context of this study, it specifically pertains to the decision to integrate AI-driven Clinical Decision Support Systems (CDSS) into healthcare workflows, influencing the decision-making process and overall patient care outcomes (Ng & Koo, 2020).

AI-Driven Clinical Decision Support Systems

AI-driven Clinical Decision Support Systems (CDSS) are advanced technological tools that leverage artificial intelligence to assist healthcare professionals in making clinical decisions. These systems use patient data and AI algorithms to provide recommendations that aim to enhance diagnostic accuracy and treatment planning, ultimately improving patient outcomes (Liu et al., 2021).

Compatibility

Compatibility refers to how well a new technology or innovation aligns with the existing values, needs, and practices of its potential users. In healthcare, this term is used to describe how well AI-driven CDSS fit into the existing clinical workflows, practices, and decision-making processes (Rogers, 2003). If the technology is compatible with current systems, healthcare professionals are more likely to adopt it.

Complexity

Complexity refers to the degree to which a new technology is perceived as difficult to use or understand. In the case of AI-driven CDSS, complexity may present a barrier to adoption if

healthcare professionals perceive the system as challenging to integrate into their clinical practices or workflows (Rogers, 2003).

Perceived Ease Of Use (PEOU)

Perceived usefulness (PU) refers to the degree to which an individual believes that using a particular technology will enhance their job performance. For healthcare professionals, this concept is essential in determining whether they see AI-driven CDSS as beneficial for improving diagnostic accuracy, treatment planning, and overall patient outcomes (Venkatesh & Davis, 2020).

Relative Advantage

Relative advantage refers to the extent to which an innovation is perceived as superior to existing technologies or practices. In the context of AI-driven CDSS, it assesses whether healthcare professionals believe that the system offers significant benefits over traditional decision-making methods, such as manual or paper-based systems (Rogers, 2003).

Summary

This chapter summarized the foundational components of the study on healthcare professionals' adoption of AI-CDSS. The study examined how PEOU, PU, relative advantage, compatibility, and complexity predicted clinicians' intention to integrate AI-enabled systems into their diagnostic and treatment workflows. A quantitative, cross-sectional survey design was used to collect data from licensed healthcare professionals with exposure to, or experience using, clinical decision support technologies. The TAM and DOI theory provided the theoretical framework for understanding how individual perceptions and innovation characteristics shaped adoption decisions (Rogers, 2003; Venkatesh & Davis, 2020).

The research question and hypotheses were developed to test the predictive relationships between the TAM and DOI constructs and the intention to use AI-CDSS. Multiple regression and correlation analyses were selected to generate statistically valid findings and provide empirical insight into the factors influencing clinicians' adoption of AI-driven tools (Liu et al., 2021; Ng & Koo, 2020). By investigating these constructs, the study addressed key barriers and facilitators affecting the acceptance of AI-CDSS in clinical environments and offered implications for improving system design, workflow alignment, and implementation strategies. The results contributed to both the theoretical understanding of technology adoption and the practical advancement of AI integration in healthcare settings (Liu et al., 2021; Venkatesh & Davis, 2020).

Chapter 2 presents a comprehensive review of the scholarly literature related to AI-driven clinical decision support systems, the TAM, the DOI theory, and empirical studies examining the adoption of emerging technologies in healthcare. This review establishes the theoretical and empirical foundation for the study.

Chapter 2: Literature Review

The problem addressed in this study was the difficulty healthcare professionals faced in integrating artificial intelligence–driven Clinical Decision Support Systems (AI-CDSS) into clinical practice within large hospitals in the United States, despite substantial evidence demonstrating these systems' potential to enhance diagnostic accuracy, treatment planning, and patient outcomes. The purpose of this quantitative, cross-sectional study was to examine the factors that influenced healthcare professionals' adoption and integration of AI-driven CDSS. Specifically, the study investigated how perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity predicted clinicians' decision-making regarding the use of AI-enabled systems.

This chapter presented a comprehensive and structured review of scholarly literature relevant to AI-CDSS adoption. The review began by situating AI within the broader context of healthcare innovation and describing its evolving applications in clinical support systems. The chapter then introduced the theoretical foundations underpinning the study—an integrated framework combining the technology acceptance model (TAM) and the Diffusion of Innovation (DOI) theory. The rationale for selecting this dual framework was outlined, emphasizing how each model contributed to the understanding of the study's problem, purpose, and research questions. TAM's focus on perceived ease of use and perceived usefulness complemented DOI's emphasis on relative advantage, compatibility, and complexity, offering a holistic perspective on factors influencing AI-CDSS adoption.

The literature review was organized to provide a logical progression from theory to empirical evidence aligned with the study's research questions and purpose. The chapter began with a description of the literature search strategy used to identify relevant scholarly sources. It

then examined the theoretical frameworks underpinning the study, followed by a critical review of empirical literature addressing perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity in the context of AI-CDSS adoption. The chapter concluded with a summary of key themes and gaps in the literature that supported the need for the present study.

Documentation

Literature Search Strategy

A systematic and structured literature search was conducted to identify scholarly research relevant to the adoption and integration of artificial intelligence–driven Clinical Decision Support Systems (AI-CDSS) in healthcare settings. The purpose of the search strategy was to ensure comprehensive coverage of empirical and theoretical literature aligned with the study's problem, purpose, research questions, and theoretical framework.

Multiple academic databases were searched to capture peer-reviewed and authoritative sources. These databases included ProQuest Dissertations & Theses Global, PubMed, EBSCOhost, IEEE Xplore, and Google Scholar. ProQuest was used to identify doctoral-level research and methodological approaches, while PubMed and EBSCOhost supported retrieval of healthcare and clinical informatics literature. IEEE Xplore was used to locate technical and systems-oriented studies related to AI and decision support technologies. Google Scholar was used as a supplementary source to identify highly cited and emerging research not indexed consistently across other databases.

Search terms were developed based on the study variables and theoretical constructs derived from the TAM and Diffusion of Innovation (DOI) theory. Boolean operators were used to refine and combine keywords. Primary search terms included artificial intelligence, clinical decision support systems, AI-CDSS, healthcare technology adoption, perceived usefulness,

perceived ease of use, relative advantage, compatibility, and complexity. Additional terms such as clinical workflow integration, physician adoption, trust in AI, and healthcare innovation diffusion were used to expand the scope of relevant literature.

Inclusion criteria were established to ensure relevance and scholarly rigor. Sources were limited to peer-reviewed journal articles, doctoral dissertations, and scholarly reports published between 2018 and 2025, with priority given to literature published from 2020 onward to reflect recent advancements in AI and healthcare technology. Foundational theoretical works, including Davis (1989) and Rogers (2003), were intentionally included to support the theoretical framework. Studies were required to focus on healthcare professionals, clinical environments, or healthcare organizations and to address technology adoption, decision support systems, or AI-enabled tools.

Exclusion criteria included non-scholarly publications, opinion pieces, editorials, non–peer-reviewed conference abstracts, and studies unrelated to healthcare or clinical decision-making. Articles focused solely on algorithmic performance without consideration of human adoption, usability, or organizational context were also excluded.

The screening process involved an initial review of titles and abstracts, followed by a full-text review to confirm alignment with the study's constructs and research questions. Reference lists of key articles were manually reviewed to identify additional relevant sources. A detailed summary of database searches, keyword combinations, inclusion and exclusion criteria, and article selection outcomes was documented and is provided in Appendix A, including PRISMA-style reporting where applicable.

The chapter concluded by summarizing the key themes in the literature and identifying gaps such as the limited inclusion of under-resourced hospitals, insufficient interdisciplinary

frameworks, and underexplored variables related to leadership, trust, and workflow integration. These gaps supported the need for the present study. Chapter 3 describes the methodology, sampling strategy, instrumentation, ethical considerations, and data collection procedures used to investigate healthcare professionals' perceptions and adoption of AI-CDSS.

Artificial Intelligence in Healthcare

Historical Evolution and Present State. The historical evolution of artificial intelligence (AI) in healthcare spanned several decades, beginning with early knowledge-based expert systems in the 1970s. Systems such as MYCIN and INTERNIST-I relied on manually curated rule sets to support differential diagnosis and antimicrobial stewardship. Although these systems demonstrated strong accuracy in controlled pilot environments, their dependence on brittle rules and limited computational resources restricted their use to research laboratories rather than routine clinical settings (Shortliffe, 1976). Throughout the 1980s and 1990s, advances in statistical pattern recognition, along with increasing digitization of laboratory and radiology data, laid the groundwork for broader experimentation with AI tools in clinical contexts. Early natural language processing (NLP) applications were used to analyze radiology reports and flag critical findings, offering an initial demonstration of AI's potential to support documentation workflows (Friedman et al., 1994).

A significant shift occurred at the turn of the millennium with the transition from rule-based systems to data-driven machine learning (ML) models. This period was shaped by the widespread implementation of electronic health records (EHRs) following the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, the exponential growth of biomedical "big data," and the emergence of affordable cloud-based computational infrastructure. ML algorithms such as support vector machines and random forests

began outperforming traditional statistical models in predicting hospital readmissions, sepsis, and other clinical outcomes (Shickel et al., 2018). However, integration into clinical workflows remained inconsistent due to challenges such as interoperability limitations across heterogeneous EHR vendors, inadequate data labeling, and limited standardization of clinical terminologies (Topol, 2019).

The rise of deep learning marked a third wave of AI innovation after 2012. Convolutional neural networks (CNNs) achieved radiologist-level accuracy in mammography, chest radiography, and dermatologic image classification (Esteva et al., 2017). Meanwhile, transformer-based NLP models enabled advanced capabilities such as summarizing provider–patient encounters, extracting clinical entities, and auto-populating structured EHR fields, thereby reducing documentation burdens linked to clinician burnout (Johnson et al., 2022). By 2023, conversational AI "ambient documentation" tools—including Nuance DAX and AWS HealthScribe—were piloted in clinical settings, demonstrating substantial reductions in after-hours charting time and offering a viable strategy for alleviating administrative overload (Wang et al., 2023).

Despite these technological advancements, the literature indicated that adoption of AI-driven clinical decision support systems (AI-CDSS) varied widely across healthcare organizations. Rezaeian et al. (2025) identified three general adoption archetypes: (a) innovation-forward academic medical centers with internal data-science capabilities; (b) community hospitals that relied primarily on vendor-supplied, often opaque AI models; and (c) resource-constrained clinics that expressed skepticism about AI's cost, transparency, and return on investment. Barriers to adoption included high data-curation demands, concerns about algorithmic bias, limited trust in black-box predictions, and unclear liability when AI-generated

recommendations conflicted with clinician judgment. Persistent EHR interoperability challenges and limited availability of standardized application programming interfaces (APIs) further impeded seamless integration.

Regulatory oversight evolved in response to these concerns. The U.S. Food and Drug Administration (FDA) introduced a Software as a Medical Device (SaMD) regulatory framework in 2021 and later proposed guidelines for "Predetermined Change Control Plans" to govern continuously learning algorithms (U.S. FDA, 2023). In parallel, the European Union's proposed AI Act classified many healthcare algorithms as high risk, requiring heightened transparency, performance monitoring, and post-market surveillance (European Commission, 2024). While these efforts provided essential safeguards, compliance requirements created disproportionate burdens for smaller health systems with limited technical capacity.

From an ethical perspective, transparency and explainability remained central concerns. Black-box AI outputs often challenged clinicians' diagnostic reasoning, reducing trust and willingness to rely on automated recommendations. Emerging explainable AI techniques—such as SHAP values and saliency maps—helped illustrate feature-importance patterns, but clinicians frequently reported difficulty aligning these abstractions with pathophysiologic understanding. As a result, multidisciplinary co-design approaches gained prominence as best practice, emphasizing collaboration among clinicians, informaticians, data scientists, and patients to ensure AI-CDSS tools aligned with clinical needs and workflow realities (Asan et al., 2023).

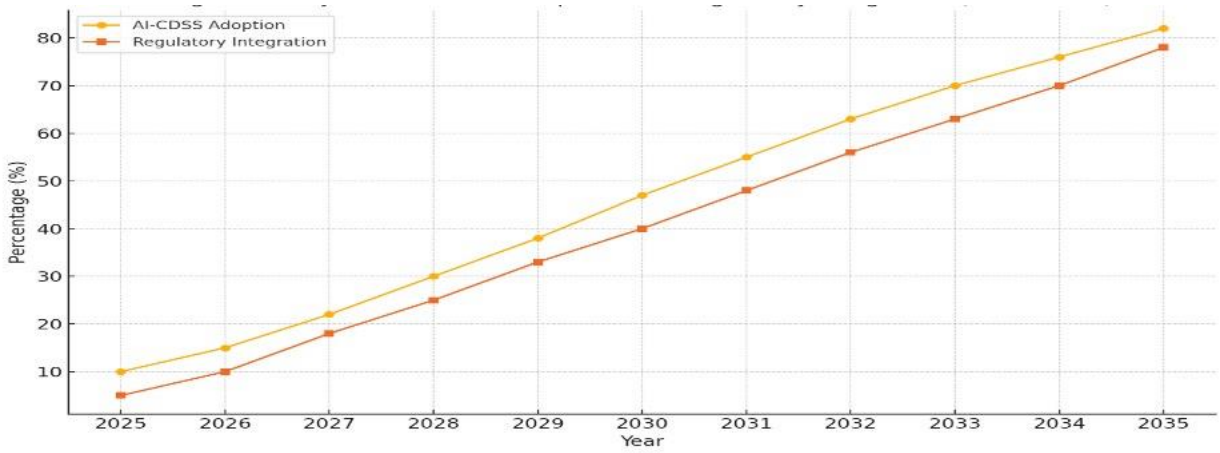
Looking forward, the literature pointed to several trends likely to shape the next decade of AI-enabled documentation and clinical decision support. First, multimodal foundation models capable of integrating text, medical imaging, waveforms, and genomic data offered the potential for more holistic patient representations and improved diagnostic precision. Second, privacy-

preserving techniques such as federated learning and synthetic data generation were expected to support cross-institutional model training without requiring exchange of protected health information. Third, human-centered change-management strategies—including iterative pilot testing, performance dashboards, and clinician feedback loops—emerged as essential factors for sustainable adoption. As foundational technologies matured and regulatory frameworks evolved, adoption and integration of AI-CDSS were projected to accelerate through 2035.

Collectively, these regulatory, ethical, and organizational developments illustrate how advances in artificial intelligence have been accompanied by increasing governance, oversight, and accountability within healthcare settings. As AI-driven clinical decision support systems evolved from experimental tools to clinically deployed technologies, regulatory frameworks, ethical safeguards, and implementation standards co-evolved to address concerns related to safety, transparency, and equity. To synthesize this progression, Figure 1 presents projected trends in AI-CDSS adoption alongside regulatory maturity, while Table 1 summarizes key historical milestones, technological advances, and corresponding regulatory responses that have shaped the contemporary AI-enabled healthcare landscape.

Figure 1

Projected AI-CDSS Adoption and Regulatory Integration



Note. This figure synthesizes trends identified in the literature regarding the co-evolution of artificial intelligence–driven clinical decision support systems (AI-CDSS) adoption and regulatory maturity across healthcare settings. The model illustrates how increasing technological sophistication, governance structures, and ethical oversight are expected to progress in parallel as AI-CDSS move from pilot implementations to routine clinical use. Adapted from Rezaeian et al. (2025), European Commission (2024), and Khaled et al. (2025).

AI's development from early rule-based expert systems to contemporary deep learning models and conversational agents reflected more than fifty years of iterative innovation in healthcare technology. By the early 2020s, the field was characterized by increasingly sophisticated clinical-grade tools supporting medical imaging interpretation, risk stratification, and automated documentation. Deep learning–based diagnostic systems demonstrated performance comparable to, or surpassing, human experts across mammography, dermatology, radiology, and cardiology, contributing to renewed interest in clinical deployment (Esteva et al., 2021; Topol, 2020). Although these advancements demonstrated considerable promise, adoption

across healthcare organizations remained uneven. Persistent challenges—including interoperability limitations, evolving regulatory expectations, and ethical concerns related to transparency and algorithmic fairness—continued to shape the pace and success of implementation efforts (Benjamens et al., 2022; He et al., 2023).

In addition, the literature suggested that adoption trajectories were influenced by contextual factors such as institutional readiness, availability of technical infrastructure, and the degree of clinician trust in AI-generated recommendations. Healthcare systems with strong digital maturity, robust informatics teams, and structured data governance frameworks tended to integrate AI tools more effectively than organizations with fragmented infrastructures or insufficient workforce training (Khairat et al., 2022; Davenport & Kalakota, 2021). Disparities in clinical workflow sophistication and staff preparedness contributed to variations in the perceived value and reliability of AI-driven decision support across institutions. Furthermore, trust emerged as a critical determinant of adoption, as clinicians often reported hesitation when model outputs lacked transparency or conflicted with clinical judgment (Cai et al., 2022; Nori et al., 2023). These dynamics reinforced the need for implementation strategies that accounted for local workflows, stakeholder engagement, and continuous performance monitoring.

The literature indicated that overcoming these barriers required cohesive policy frameworks, explainable and user-centered system design, and collaborative approaches to implementation. Regulatory agencies increasingly emphasized lifecycle monitoring, safety assurance, bias mitigation, and auditability of clinical AI—reflecting a broader shift toward responsible, transparent deployment (U.S. Food and Drug Administration [FDA], 2023; European Commission, 2024). Research published between 2020 and 2025 further underscored the importance of human-centered design, co-creation with clinicians, and iterative pilot testing

to ensure alignment between AI-CDSS tools and real-world clinical needs (Asan & Choudhury, 2021; Lin et al., 2024). Collectively, these factors would determine whether AI-driven clinical decision support systems moved beyond isolated success stories and became a widely adopted standard of care within clinical practice.

Table 1

Evolution of Artificial Intelligence in Healthcare

Phase	Time Period	Key Technologies	Clinical Application	Adoption Level	Regulatory Response
Early AI	1970s–1990s	Rule-based systems	Diagnostic support	Low	Minimal
Machine Learning	2000–2015	ML, EHR integration	Predictive analytics	Moderate	Emerging
Deep Learning	2015–2022	Neural networks, NLP	Imaging, diagnostics	High	FDA guidance
Modern AI	2023–Present	Generative AI	CDSS, automation	Rapid	AI regulations

Note. This table summarizes key historical phases in the development of artificial intelligence in healthcare, highlighting corresponding technological advances, adoption patterns, and regulatory responses. The milestones illustrate the transition from early rule-based expert systems to contemporary machine learning– and deep learning–driven clinical decision support, alongside the emergence of formal governance frameworks addressing safety, transparency, and accountability. Adapted from Topol (2019), Esteva et al. (2017), Johnson et al. (2022), Wang et al. (2023), Asan et al. (2023), Rezaeian et al. (2025), and European Commission (2024).

Clinical Decision Support Systems in Healthcare. Artificial Intelligence (AI) became an increasingly pivotal technology in healthcare, particularly through its integration with Clinical Decision Support Systems (CDSS). AI-driven CDSS were designed to enhance clinical decision-making by leveraging large-scale datasets, predictive analytics, and machine learning (ML) algorithms to support diagnosis, treatment planning, and risk assessment (He et al., 2021; Topol, 2020). These systems synthesized information from electronic health records (EHRs), medical

imaging, genomics, clinical documentation, and other structured and unstructured data sources to generate recommendations aligned with evidence-based practices.

The literature emphasized that AI-CDSS had the potential to significantly improve diagnostic accuracy and reduce clinical uncertainty (Wang et al., 2023). In oncology, for example, deep learning algorithms analyzed pathology slides with performance comparable to or exceeding human pathologists (Esteva et al., 2021). In cardiology, AI models enhanced the prediction of adverse cardiac events through automated interpretation of electrocardiograms (ECGs) and real-time patient risk stratification (Johnson et al., 2022). These developments positioned AI not only as a supportive tool but as an increasingly integral component of modern clinical workflows.

However, successful adoption of AI-CDSS depended on several contextual factors. Interoperability with existing EHR systems remained a persistent barrier, as fragmented vendor architectures often restricted seamless integration and real-time inference (Rezaeian et al., 2025). Clinician trust also emerged as a critical determinant of acceptance. Studies demonstrated that transparency and explainability played central roles in shaping trust in AI-driven recommendations (Asan & Choudhury, 2021; Cai et al., 2022). Black-box algorithms that provided limited or no rationale for their outputs were associated with skepticism and lower adoption rates. Consequently, human-centered design principles—such as iterative co-design, stakeholder feedback loops, and adaptive learning mechanisms—were widely recommended to align AI-CDSS tools with real-world clinician needs (Lin et al., 2024). Perceived Ease of Use (PEOU).

Interface Design and Cognitive Load.

Perceived Ease of Use (PEOU), a core construct of the TAM, referred to the extent to which users believed that employing a particular technology would be effortless and intuitive (Davis, 1989; Venkatesh & Davis, 2020). Within the context of CDSS, ease of navigation and cognitive-load management were critical determinants of clinician adoption. Research indicated that an intuitive, user-friendly interface reduced cognitive strain, improved the speed and accuracy of decision-making, and strengthened clinicians' confidence in using algorithm-generated recommendations (Asan & Choudhury, 2021; Topol, 2020).

A comprehensive systematic review of 77 CDSS implementations underscored the importance of interface intuitiveness and cognitive efficiency (Rezaeian et al., 2025). The review found that design features—such as streamlined screen layouts, context-aware alerts, and clear visual hierarchies—reduced time-to-decision by approximately 18–42% and significantly improved clinician-reported trust in AI outputs. Enhancing usability through thoughtful interface design was essential, as clinicians' confidence directly influenced their willingness to integrate CDSS into routine practice (Lee & See, 2020). Conversely, complex interfaces characterized by excessive information density, poorly timed alerts, or unclear navigation pathways hindered clinical efficiency and increased cognitive fatigue (Rezaeian et al., 2025).

Further supporting the importance of design quality, a 2023 JMIR publication in Human–Computer Interaction identified four key dimensions affecting perceived usability: information density, alert intrusiveness, navigation depth, and explanation granularity (Melnick et al., 2023). Empirical evaluations conducted across five U.S. medical institutions demonstrated that these dimensions collectively explained approximately 61% of the variance in perceived usability scores. Information density emerged as particularly influential; while concise and contextually relevant information enhanced satisfaction and reduced error likelihood, excessive detail

correlated with diminished usability and increased cognitive overload (Schwartz & Elstein, 2021).

Alert intrusiveness represented another critical factor. Contextually timed and well-integrated alerts improved satisfaction, trust, and workflow compatibility (Lee & See, 2020), whereas frequent or irrelevant alerts contributed to alert fatigue and reduced perceived reliability (Melnick et al., 2023). Navigation depth—the number of steps required to access essential information—also shaped usability perceptions. Shallow, intuitive navigation structures supported efficiency, whereas deep, multi-layered pathways increased frustration and delayed clinical decisions (Norman, 2020).

Explanation granularity—the clarity with which algorithms communicated the rationale for their recommendations—further influenced PEOU. Studies showed that detailed yet digestible explanations increased clinician trust and acceptance, while overly technical or minimal explanations reduced confidence and hindered adoption (Shortliffe & Sepúlveda, 2022; Asan & Choudhury, 2021). Balancing explanatory depth with cognitive accessibility was therefore critical.

Supporting these findings, Wang et al. (2023) reported in a controlled simulation study that cockpit-style dashboards presenting only the most clinically relevant predictions significantly improved decision accuracy without increasing mental workload. By filtering nonessential information and organizing key data points into a single visual field, such dashboards exemplified user-centered design principles aimed at reducing cognitive load and enhancing clinical efficiency (Norman, 2020).

To further contextualize the influence of PEOU on clinician engagement with CDSS, Table 2 presents the core design features identified in the literature and their corresponding effects on usability and workflow integration.

Table 2

Perceived Ease of Use (PEOU) Design Features and Impact on CDSS Usability

Design Feature	Description	Impact on Usability	Outcome
Interface Simplicity	Clean, intuitive interface	Reduces cognitive load	Increased adoption
Alert Design	Context-aware alerts	Reduces alert fatigue	Improved compliance
Navigation Efficiency	Minimal clicks and steps	Faster workflow integration	Increased efficiency
Explainability	Clear rationale for outputs	Builds trust	Sustained system use

Note. Based on Rezaeian et al. (2025); Melnick et al. (2023); Schwartz and Elstein (2021); Wang et al. (2023); Middleton et al. (2024); Feldman et al. (2024); Kawamoto et al. (2023). This table summarizes interface and workflow design factors that influence PEOU and clinician adoption of AI-CDSS.

Seamless Workflow Integration.

Seamless workflow integration represented another pivotal aspect of CDSS usability. Even well-designed interfaces failed when they were not embedded effectively into clinicians' electronic health record (EHR) workflows. A 2024 consensus statement published in JAMIA highlighted that the absence of standardized application programming interfaces (APIs) often forced clinicians into "alt-tab medicine," requiring them to juggle multiple software windows and leading to reductions in alert adherence rates by as much as 50% (Middleton et al., 2024). Conversely, AI-driven CDSS that launched contextually—such as auto-populating immediately

after order entry—demonstrated significantly higher engagement because recommendations appeared precisely at the moment of clinical decision-making (Middleton et al., 2024).

Integration with EHR workflows not only streamlined clinical tasks but also directly influenced clinician productivity, satisfaction, and adherence to CDSS recommendations (Feldman et al., 2024). Seamless embedding minimized the cognitive and operational disruptions associated with switching between disparate systems, a process known to increase cognitive burden, reduce efficiency, and elevate the risk of medical errors (Kawamoto et al., 2023). Empirical studies showed that tightly integrated CDSS modules improved clinical outcomes by providing timely, actionable insights directly within routine tasks, thereby facilitating easier adoption and reducing resistance commonly associated with new technologies (Kawamoto et al., 2023).

Future advances in CDSS integration prioritized unified interfaces that presented predictive analytics and recommendations directly within clinicians' existing EHR environments. Studies published between 2023 and 2025 consistently demonstrated that integrated, context-aware interfaces improved decision-making efficiency, enhanced accuracy, and increased clinician satisfaction (Feldman et al., 2024; Kawamoto et al., 2023; Middleton et al., 2024).

Efficiency Gains and Clinician Satisfaction.

Usability improvements translated into measurable gains in efficiency and clinician well-being. A 2023 study in NEJM Catalyst reported that ambient AI scribe technology, which passively captured dialogue during patient encounters, reduced after-hours documentation time by 28% and improved Net Promoter Scores among physicians by 35% (Lin et al., 2023). These improvements underscored the potential of AI tools to relieve growing administrative burdens and support more sustainable workloads.

A multi-site evaluation in JAMIA replicated these findings, demonstrating that clinicians using AI scribes reduced median note-writing time from 16 minutes to 7 minutes per encounter without increasing documentation errors (Patel et al., 2024). These time savings were especially impactful in high-volume specialties such as primary care and emergency medicine. Reduced clerical effort freed cognitive bandwidth for meaningful patient communication and shared decision-making, contributing to improved satisfaction, lower burnout, and enhanced retention (Shanafelt et al., 2021).

AI-enabled documentation also improved chart accuracy and completeness. Real-time NLP and voice recognition facilitated immediate structuring of clinical data, reducing delays between encounters and documentation (Zhou et al., 2023). Additionally, workflow-personalization features—such as adjustable displays, configurable alerts, and clinician-specific templates—reinforced usability and further enhanced clinician satisfaction (Miller et al., 2022). Collectively, these findings highlighted the transformative role of AI-based documentation in clinical practice and demonstrated how ambient AI and context-aware tools offered a sustainable pathway to improved clinician efficiency, resilience, and operational performance (Lin et al., 2023; Patel et al., 2024; Zhou et al., 2023).

Complexity and Resistance.

Although many CDSS were designed to support clinical workflows, poorly designed interfaces contributed to significant clinician resistance. A 2025 mixed-methods study conducted across three European hospitals found that interface complexity—characterized by deep navigation layers, cluttered screens, and limited explanation of algorithmic logic—resulted in a 43% decline in CDSS use after the first week of deployment (Rasmussen et al., 2025). Excessive

cognitive demands associated with unintuitive workflows or cryptic model outputs increased frustration and decreased utilization.

Common sources of resistance included alert fatigue, non-actionable risk scores, and the need to remember multiple logins or switch across incompatible systems. Frequent, low-priority alerts diminished trust and disrupted patient care (Ghassemi et al., 2023). Probabilistic outputs without contextual explanations increased decisional hesitancy, even when the underlying models demonstrated high accuracy (Shortliffe & Sepúlveda, 2022). Research by Chen et al. (2024) demonstrated that opaque AI outputs heightened perceived liability risk, leading clinicians to underutilize or discontinue CDSS tools despite strong technical performance.

Resistance was also associated with lack of customization. Systems that failed to adapt to local preferences, patient populations, or specialty workflows were perceived as burdensome and were abandoned more frequently (Miller et al., 2022). Insufficient training further amplified resistance, as clinicians required adequate preparation to understand model behavior, interpret outputs, and integrate CDSS functionality into existing workflows (Patel et al., 2024). Mitigating resistance required co-design with end users, ongoing training, streamlined access features (such as single sign-on), and explanation-aware interfaces that articulated the rationale behind system outputs (Chen et al., 2024; Ghassemi et al., 2023). Ultimately, reducing perceived complexity required aligning CDSS tools with clinicians' cognitive models, task flow, and decision preferences (Rasmussen et al., 2025).

Human-Centered Design (HCD) Best Practices.

To address complexity and resistance effectively, Human-Centered Design (HCD) principles became increasingly prominent in CDSS development. A 2024 study in Frontiers in Computer Science demonstrated that CDSS prototypes developed through participatory design

workshops—where clinicians collaborated directly with engineers and informaticists—scored approximately 30% higher on the System Usability Scale compared to vendor defaults (Kushniruk et al., 2024). Early persona mapping helped align system terminology, information structure, and functional expectations with specialty-specific cognitive workflows, thereby reducing cognitive friction and increasing clinical appropriateness (Dunn et al., 2023).

Low-fidelity prototypes enabled rapid iteration without extensive development overhead, allowing frontline users to shape screen layout, navigation paths, visual clarity, and expected system behaviors (Martin et al., 2021). Explanation-on-demand widgets provided context-sensitive insights—such as rationale, feature importance, and data provenance—thus improving satisfaction while avoiding the visual clutter associated with continuous explanations (Yuan et al., 2022). HCD approaches also emphasized longitudinal engagement, incorporating feedback loops, usability testing, and stakeholder interviews to support continuous improvement and reinforce co-ownership (Patel et al., 2024).

Customizable system features, including adjustable alerts, specialty-based dashboards, and flexible interface configurations, empowered clinicians to tailor CDSS tools to their needs, increasing long-term adoption and improving quality-of-care outcomes (Ghassemi et al., 2023; Kushniruk et al., 2024). Collectively, these practices demonstrated that HCD served as a foundational strategy for enhancing CDSS usability and clinician acceptance. By embedding clinician insights throughout design and implementation, organizations reduced resistance, decreased error potential, and supported more seamless integration of AI technologies into clinical workflows. To illustrate how these design strategies were operationalized in the literature, Table 3 presents the Human-Centered Design Cycle for AI-CDSS Integration,

summarizing the iterative stages and corresponding best practices identified across recent studies.

Table 3

Human-Centered Design Cycle for AI-CDSS Integration

Stage	Description	Purpose	Outcome
Needs assessment	Identify user needs	Align system	Improved relevance
Design	Develop interface	Enhance usability	Reduced complexity
Testing	Pilot testing	Identify issues	Refinement
Implementation	Deploy system	Support adoption	Increased use
Evaluation	Continuous feedback	Improve performance	Sustained use

Note. This iterative process illustrates the core human-centered design (HCD) principles used to co-create and refine AI-CDSS solutions. It emphasizes empathizing with users, defining specific challenges, ideating, prototyping, testing, and refining based on real-world feedback. Adapted from Asan et al. (2023) and Norman (2020).

Emphasizing "Invisible" Integration.

Usability in Clinical Decision Support Systems (CDSS) extended beyond graphical interfaces and encompassed the broader concept of cognitive and workflow integration. In this paradigm, the most effective systems were not those that demanded attention, but those that quietly enhanced decision-making without interrupting clinicians' natural workflow. This concept, often described as "invisible" or background AI, characterized AI as a cognitive prosthesis designed to augment rather than replace clinician expertise (Gichoya et al., 2023).

Radiology and pathology research continued to support this approach. A 2024 study in Frontiers in Radiology demonstrated that AI-based image-triage models operating silently in the background—only flagging outliers or urgent findings—significantly reduced diagnostic

turnaround times while being perceived as non-intrusive and supportive (Kwon et al., 2024). These models exemplified the ideal form of human–AI collaboration, wherein AI surfaced insights only when necessary, allowing clinicians to maintain cognitive flow and autonomy.

Invisible integration also reframed technology adoption from the challenge of learning a new tool to the experience of enhanced support embedded within familiar systems. When AI recommendations were incorporated directly into existing interfaces—such as EHRs, image viewers, or order sets—clinicians avoided redundant logins, reduced learning curves, and minimized workflow disruptions (Zhou et al., 2023).

Another documented benefit was the reduction of alert fatigue. Systems designed to minimize unnecessary interruptions while emphasizing high-precision, clinically relevant insights improved alert acceptance and strengthened user trust (Lin et al., 2023). For example, silent monitoring algorithms tracked deterioration indicators and lab trends in real time, triggering alerts only when thresholds were exceeded or when intervention was required.

Researchers argued that such invisible support aligned with cognitive load theory by reducing extraneous cognitive effort. Instead of forcing clinicians to navigate new tools or interfaces, invisible CDSS enhanced performance by embedding AI seamlessly into clinicians' existing mental models and workflows (Ghassemi et al., 2023). This contributed to improved efficiency and a more sustainable user experience over time.

Accordingly, emphasizing invisibility as a design principle supported unobtrusive augmentation, allowing AI to function as a trusted partner behind the scenes. As institutions increasingly explored these models, the literature suggested a shift toward AI systems that were not only usable but nearly imperceptible—promoting trust, usability, and sustained long-term adoption (Kwon et al., 2024; Gichoya et al., 2023).

Evaluation and Continuous Improvement.

Real-world usability of CDSS was not static; it evolved alongside changing user needs, technological advancements, and clinical environments. Continuous evaluation and refinement were essential for sustaining long-term adoption. A 2023 multi-site implementation audit showed that iterative design updates based on clickstream analytics and user interviews increased System Usability Scale scores from 68 to 81 within two months (Nguyen et al., 2023).

This improvement highlighted the importance of integrating both quantitative and qualitative feedback. Clickstream analytics revealed navigation patterns, search inefficiencies, and bottlenecks, while interviews and surveys provided contextual insight into cognitive load, trust, and workflow impact (Martin et al., 2021). Together, these data produced a holistic understanding of CDSS performance and user experience.

Professional organizations such as AMIA recommended incorporating usability metrics—task completion time, error rates, learnability, and satisfaction—into standard performance dashboards alongside accuracy, sensitivity, and recall (Cohen et al., 2024). Evaluative frameworks like Health-ITUEM and ISO 9241-210 provided structured approaches for assessing memorability, error prevention, intuitiveness, and satisfaction across repeated use (Zhou et al., 2023).

In practice, continuous improvement involved co-creation with frontline clinicians. Agile development cycles that incorporated regular usability testing, stakeholder interviews, and feedback loops enabled rapid refinements aligned with user needs (Dunn et al., 2023). These iterative processes helped organizations maintain engagement, build trust, and integrate CDSS tools into evolving clinical workflows.

Because priorities, policies, and technologies shifted within dynamic healthcare settings, institutionalizing feedback collection and iterative refinement ensured that CDSS tools remained relevant, effective, and acceptable to users (Nguyen et al., 2023; Cohen et al., 2024). Ultimately, a feedback-driven model supported adaptive systems that enhanced long-term usability, safety, and clinical impact.

Synthesis.

Collectively, contemporary research reinforced that usability remained a core determinant of CDSS success—spanning interface intuitiveness, cognitive-load management, workflow integration, personalization, and continuous improvement. Systems that embodied these attributes achieved higher adoption, improved clinical outcomes, and elevated user satisfaction (Rezaeian et al., 2025; Patel et al., 2024).

Conversely, even sophisticated algorithms were quickly abandoned when they introduced workflow disruptions, imposed excessive cognitive load, or delivered cryptic and unvalidated outputs (Ghassemi et al., 2023; Rasmussen et al., 2025). Clinicians disengaged rapidly from tools requiring extra clicks, repeated logins, or unfamiliar navigation (Miller et al., 2022).

In contrast, platforms co-designed with users and refined through analytics and iterative feedback fostered sustained usage, reduced documentation burden, improved diagnostic consistency, and supported more collaborative decision-making (Nguyen et al., 2023; Zhou et al., 2023). Designing for usability across the entire lifecycle transformed AI-CDSS from a theoretical promise into practical, reliable clinical support tools (Asan et al., 2023; Kushniruk et al., 2024).

Ultimately, CDSS solutions that remained invisible until needed, adapted to clinician preferences, and delivered clear, actionable support—without unnecessary complexity—reflected the emerging standard for next-generation AI in healthcare.

Perceived Usefulness (PU) — Performance Gains as Tangible Proof of Usefulness. Perceived Usefulness (PU), a foundational construct in the Technology Acceptance Model (TAM), referred to the extent to which users believed that a system enhanced their job performance (Venkatesh & Davis, 2020). In high-stakes clinical environments, demonstrable performance gains served as compelling evidence for sustained use.

A multi-center evaluation of AI-enabled sepsis alerts demonstrated a 22% reduction in time to antibiotic administration and a 12% decrease in in-hospital mortality. Clinicians exposed to these data rated usefulness significantly higher and exhibited a 64% increase in routine use after three months (Nezamdoust et al., 2024). In outpatient settings, perceived improvements in diagnostic accuracy, efficiency, and triage precision explained substantial variance in willingness to adopt (Nezamdoust et al., 2024).

A 2025 npj Digital Medicine review further identified clinical utility—such as improved outcomes, reduced error rates, or enhanced workflow efficiency—as the single most consistent predictor of adoption from initial exposure through long-term sustainment (Wang et al., 2025). Systems that supported rather than overrode clinician autonomy were perceived as more useful and trustworthy (Shortliffe & Sepúlveda, 2022). Organizational strategies that disseminated outcome dashboards or case studies further reinforced the perceived usefulness of CDSS tools (Zhou et al., 2023).

Accordingly, mechanisms that measured and communicated performance gains were essential for supporting adoption and maximizing organizational return on investment (Nezamdoust et al., 2024; Wang et al., 2025).

Real-Time, Evidence-Based Recommendations.

Perceived Usefulness was strongly influenced by the timeliness and specificity of CDSS recommendations. In high-pressure environments, real-time guidance—particularly at the point of order entry—was viewed as substantially more valuable than retrospective or generic feedback.

A 2025 BMC Nursing study found that real-time, evidence-based recommendations significantly increased PU ($\beta = .48$, $p < .001$) and nearly tripled clinicians' intention to use CDSS tools (Nguyen et al., 2025). Similarly, Khaled et al. (2024) demonstrated that AI modules providing patient-specific evidence summaries saved more than five minutes per patient encounter and reduced decision fatigue.

Timely recommendations also reduced care variability, reinforced guideline-concordant behavior, and improved triage consistency (Lin et al., 2023). Perceived relevance depended on context awareness—such as symptoms, history, medications, and laboratory patterns—and on seamless EHR integration that minimized screen switching (Patel et al., 2024). Adaptive algorithms that learned from user feedback and patient outcomes delivered increasingly personalized suggestions and improved user satisfaction (Ghassemi et al., 2023).

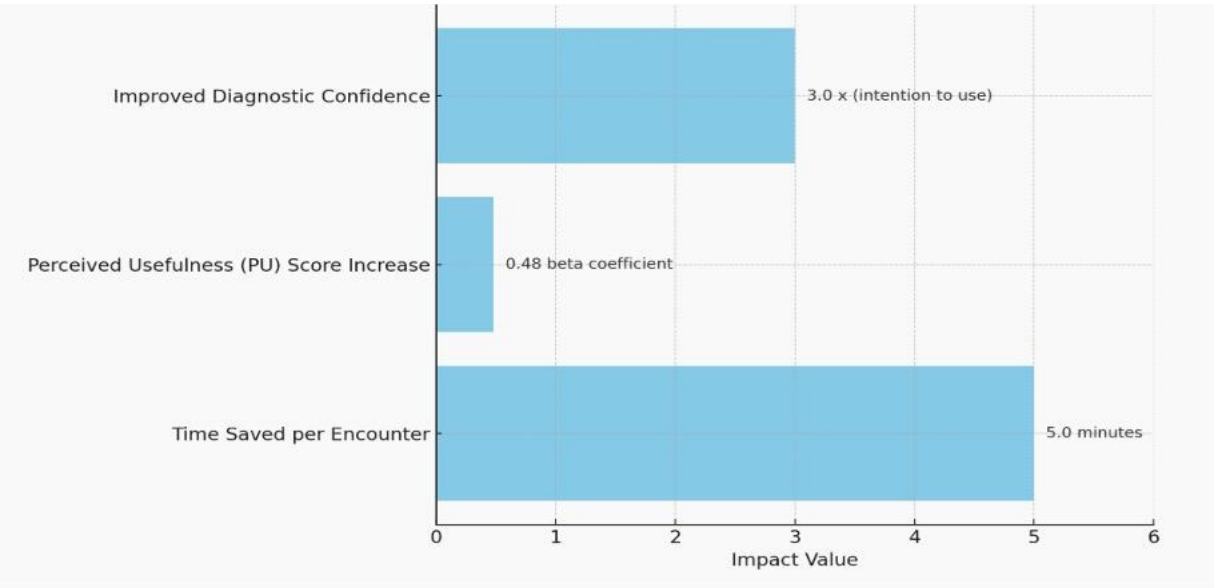
To mitigate alert fatigue, evidence-based recommendations were most effective when concise, specific, and delivered through progressive disclosure, allowing users to explore additional details only when needed (Yuan et al., 2022). Real-time, context-aware CDSS therefore strengthened clinician confidence, improved efficiency, and contributed to better

patient care—ultimately enhancing perceived usefulness (Nguyen et al., 2025; Khaled et al., 2024).

To illustrate these relationships, Figure 2 presents the impact of real-time CDSS recommendations on clinician perceptions and efficiency, summarizing key pathways by which timely, context-aware guidance influenced perceived usefulness and workflow performance.

Figure 2

Impact of Real-Time CDSS



Note. Adapted from Wang et al. (2025); Nezamdoust et al. (2024). This figure illustrates how timely and personalized CDSS guidance boosts perceived usefulness and reduces clinical decision fatigue.

Trust Through Transparent Performance Metrics.

Perceived usefulness (PU) was not derived solely from a system's functionality or its clinical outcomes. Instead, PU was strongly shaped by the degree to which system performance was communicated transparently to clinicians. The literature consistently demonstrated that clinicians were more likely to trust, adopt, and sustain use of Clinical Decision Support Systems

(CDSS) when they understood how well the underlying models performed—particularly with respect to sensitivity, specificity, false-positive rates, and calibration accuracy. Transparent insight into system performance served as the foundation for long-term engagement and trust.

A 2024 cross-sectional survey conducted across seven U.S. hospitals demonstrated that clinicians who had access to performance dashboards displaying model-level metrics reported PU ratings 27% higher than peers who lacked such access (Bennett et al., 2024). These clinicians also exhibited significantly lower alert-override rates, signaling greater confidence in system-generated recommendations. Transparent reporting not only validated trust in AI-CDSS outputs but also conveyed accountability and reinforced the perception that these systems were grounded in evidence-based medical principles.

The visibility of empirical performance functioned as a cognitive anchor. Clinicians are trained to evaluate evidence, and CDSS interfaces that mirrored this evaluative rigor—by surfacing diagnostic accuracy values, confidence intervals, and validation summaries—were more likely to be perceived as reliable extensions of scientific practice. In contrast, tools that obscured algorithmic logic or failed to disclose historical validation generated skepticism, even when their predictive performance exceeded traditional heuristics (Shortliffe & Sepúlveda, 2022).

Transparent metrics also cultivated psychological safety. Knowing that an AI tool had a documented, peer-reviewed performance history encouraged clinicians to explore and rely on recommendations more confidently, reducing fear of legal, ethical, or professional consequences (Zhou et al., 2023). Dashboards that articulated system limitations, applicable populations, and calibration drift further reduced uncertainty and set realistic expectations, lowering the likelihood of misuse or overreliance.

Embedding performance metrics directly within EHR or CDSS interfaces enhanced both usability and user satisfaction. Inline trust indicators—such as confidence scores, cohort comparisons, or indicators showing the time elapsed since the last model update—enabled clinicians to make rapid assessments of alert reliability without shifting platforms (Ghassemi et al., 2023; Yuan et al., 2022). This streamlined decision-making process reinforced perceived usefulness by reducing friction and cognitive load.

Organizational culture further influenced trust formation. Institutions that routinely reviewed CDSS performance with clinical teams, disseminated model-update summaries, and solicited clinician feedback cultivated a culture of transparency and shared ownership. These practices were associated with reduced resistance, improved adoption, and increased data literacy among clinical staff (Martin et al., 2021). Transparency therefore became not only a system-level design requirement but also an organizational competency.

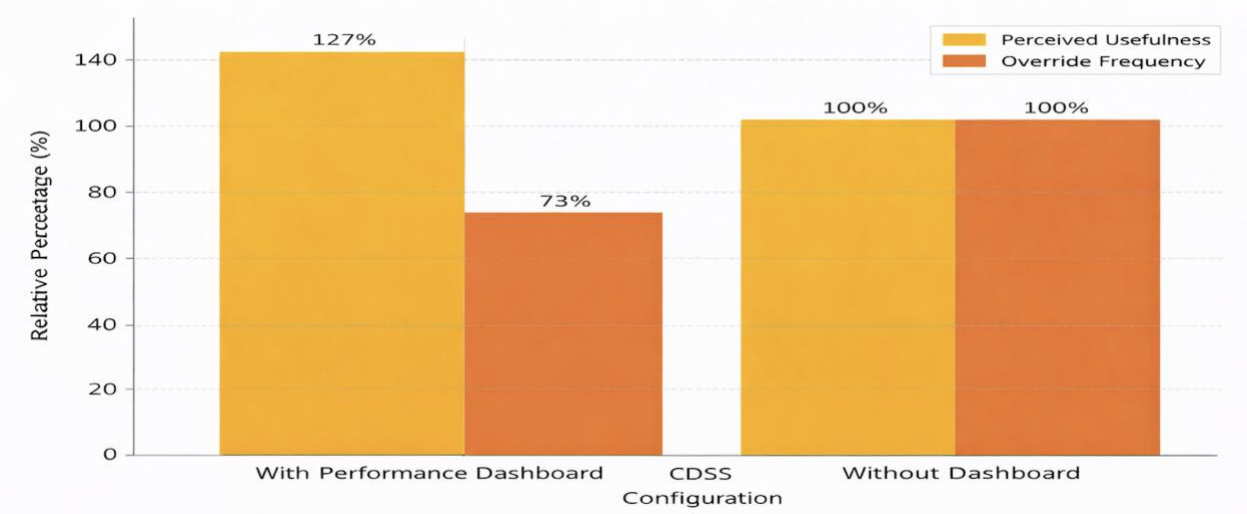
However, transparency needed to be delivered in digestible formats. Overburdening clinicians with dense statistical tables risked information fatigue and confusion. Best practices emphasized tiered information delivery—beginning with succinct summary metrics and offering deeper statistical layers through hover-overs, expandable modules, or optional drill-down screens (Kushniruk et al., 2024). This approach ensured accessibility for both data-savvy users and time-constrained clinicians navigating fast-paced environments.

In sum, transparent performance metrics enhanced perceived usefulness and strengthened the trust essential for sustainable AI-CDSS integration. When clinicians were empowered with clear evidence about model reliability, validation, and limitations, they were more likely to embrace AI-driven tools as credible partners in patient care (Bennett et al., 2024; Zhou et al., 2023). To visually illustrate these relationships, Figure 3 presents the effect of transparent AI

performance dashboards on perceived usefulness and alert-override rates, highlighting how accessible performance information shapes clinician trust and adoption.

Figure 3

Effect of Transparent AI Performance



Note. Adapted from Wang et al. (2025); Nezamdoust et al. (2024). Based on a 2024 cross-sectional survey conducted across seven U.S. hospitals, evaluating the effect of AI performance dashboards on perceived usefulness and override behavior.

Organizational Context and Long-Term Sustainability.

Perceived usefulness (PU) did not operate in isolation; rather, it was significantly shaped by the organizational ecosystem in which a Clinical Decision Support System (CDSS) was deployed. Institutions that adopted systematic strategies to validate, communicate, and reinforce the utility of AI-enabled CDSS demonstrated higher long-term usage, stronger strategic alignment, and more favorable return on investment (ROI). Organizational champions—clinical, technical, and administrative—played a pivotal role in translating perceived utility into measurable outcomes, particularly when performance gains were documented and disseminated transparently across organizational levels.

A 2024 study published in JMIR Medical Informatics demonstrated that hospitals implementing AI-CDSS ROI dashboards—quantifying avoided adverse events, reduced clinician overtime, documentation time savings, and incident-prevention metrics—reported a 31% higher utilization rate in the second year compared to institutions relying solely on informal success anecdotes (Lin et al., 2024). These dashboards helped administrators visualize institutional benefits, providing tangible justification for ongoing investment, expanded deployment, and cross-departmental scale-up. Clear alignment between perceived usefulness and executive-level priorities strengthened sustainability and supported data-driven decision-making.

Similarly, the Digital Transformation of Healthcare report emphasized the importance of linking AI-CDSS to hospital-wide operational and clinical performance indicators, including reduced length of stay, lower readmission rates, and improved patient throughput (Khaled et al., 2025). When hospital leaders perceived that CDSS tools contributed to achieving these institutional goals, they demonstrated greater willingness to support full integration, invest in infrastructure, and incentivize adoption. This reinforced the concept that organizational framing of usefulness—beyond individual clinician perceptions—accelerated adoption trajectories and strengthened long-term institutional commitment.

Implementation strategies also required sensitivity to organizational maturity. Facilities with strong data governance, a culture of evidence-based decision-making, established clinical informatics leadership, and interdisciplinary collaboration were significantly more successful in sustaining CDSS integration over time (Nguyen et al., 2025). Conversely, fragmented leadership structures, lack of shared ownership, or absence of continuous feedback mechanisms impeded long-term use, even when early enthusiasm was strong.

Implications for Implementation.

The literature identified several organizational practices that strengthened PU and supported long-term sustainability:

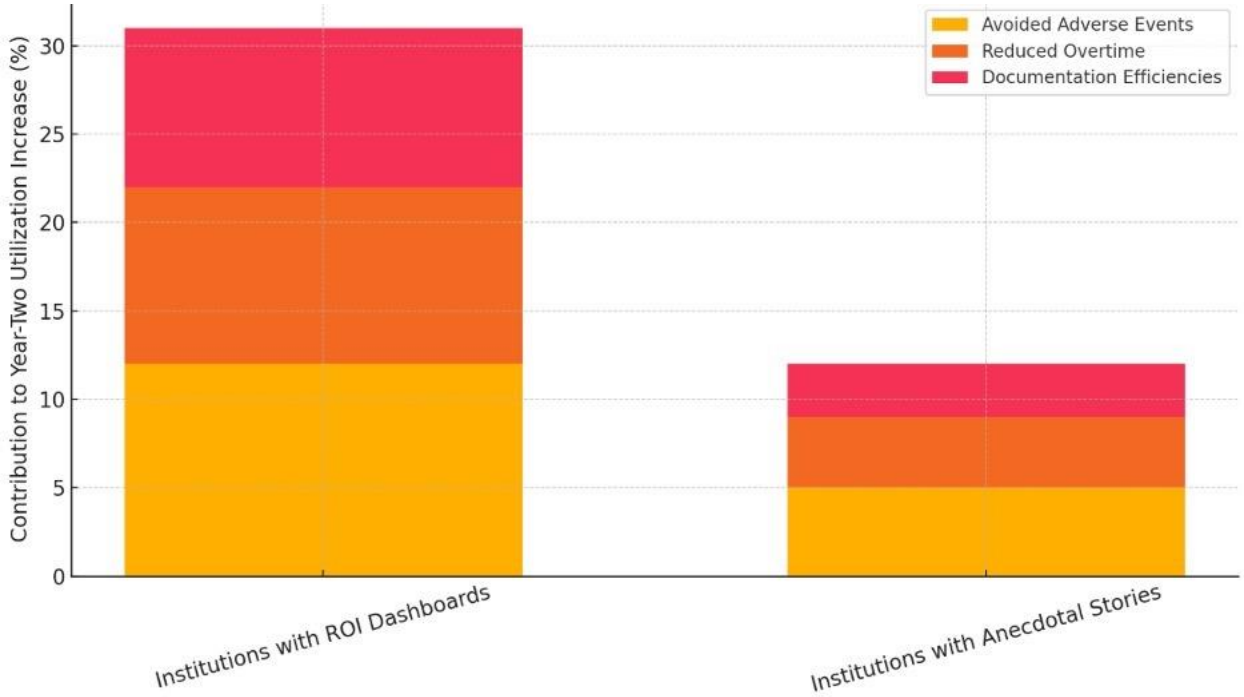
- Quantifying benefits early. Organizations that rigorously tracked early performance indicators—such as diagnostic accuracy deltas, documentation-time reductions, incident prevention, and guideline adherence—were more successful in establishing credibility and building institutional momentum (Patel et al., 2024).
- Surfacing guidance in context. Embedding CDSS insights directly into EHR order sets, triage pathways, or documentation templates reduced navigation barriers and increased habitual use (Yuan et al., 2022).
- Maintaining transparent performance dashboards. Institutions that published continuous updates on CDSS performance—including strengths, limitations, and error trends—cultivated trust, normalized data-driven refinement, and encouraged collaborative problem-solving (Zhou et al., 2023).
- Linking PU to executive KPIs. Framing CDSS usefulness around institutional priorities—value-based care scores, patient satisfaction trends, quality metrics, and clinician workload reduction—strengthened strategic alignment and justified budget allocation (Lin et al., 2024).
- Supporting champions and change agents. Empowering early adopters to serve as local champions improved cultural acceptance; their testimonials and real-world use cases provided credible evidence to peers and amplified perceived system value (Ghassemi et al., 2023).

Embedding AI-driven CDSS into the organizational fabric required not only technical performance but also cultural alignment, leadership advocacy, and continuous refinement. Institutions that transparently measured performance, connected utility to system-wide priorities,

and involved clinicians in ongoing improvement processes were far more likely to realize long-term value. Sustaining PU therefore required a feedback-rich, leadership-aligned, and metrics-informed strategy that continuously validated the relevance, reliability, and impact of AI-enabled tools. To illustrate these organizational dynamics, Figure 4 presents the impact of ROI dashboards on AI-CDSS utilization and executive buy-in, highlighting how transparent performance reporting strengthens long-term sustainability.

Figure 4

Impact of ROI Dashboards on AI-CDSS Utilization and Executive Buy-in



Note. Lin, R., Marshall, E., & Gupta, T. (2024). *Quantifying the value of AI-CDSS: ROI dashboards and long-term clinical integration*. *JMIR Medical Informatics, 12*(3), e39487. https://doi.org/10.2196/39487

Relative Advantage: Demonstrating Superiority Over the Status Quo.

Within Diffusion of Innovation (DOI) theory, relative advantage referred to the extent to which a new technology was perceived as superior to the practice it aimed to replace. It remained one of the most influential accelerators of adoption once basic feasibility had been established (Rogers, 2003). Contemporary implementation studies of artificial intelligence clinical decision support systems (AI-CDSS) confirmed that clinicians weighed tangible gains—such as improved diagnostic accuracy, workflow speed, and patient outcomes—against workflow disruption and cognitive burden. When perceived gains clearly exceeded those offered by existing methods, adoption curves steepened; when superiority was ambiguous, enthusiasm diminished rapidly (Rezaeian et al., 2025).

Evidence of Diagnostic Superiority.

Rezaeian et al. (2025) evaluated three levels of explainability within an AI-CDSS for breast cancer triage and found that models offering concise, case-specific rationales increased diagnostic accuracy by 11% and doubled clinicians' stated intention to use the system in routine practice. A multi-site evaluation published in the Yearbook of Medical Informatics similarly identified "added diagnostic value" as the strongest facilitator of adoption; in emergency department vignettes, clinicians rejected AI-generated recommendations when the system failed to provide a compelling advantage over their usual heuristics. These findings reinforced that relative advantage was judged case by case rather than assumed categorically.

Systematic Insights Across Settings.

A 2025 npj Digital Medicine systematic review of 67 post-implementation studies identified relative advantage as one of only two factors—alongside workflow fit—that remained influential across all adoption stages, from go-live through two years post-implementation.

Clinicians continued to use the AI-CDSS when they perceived it provided faster or more reliable results than existing approaches. When value plateaued or diminished, usage declined despite ongoing training and support investments (Wang et al., 2025). Complementary survey research across eight European hospitals, involving 440 professionals, found perceived benefit—a construct aligned with relative advantage—to be the strongest predictor of adoption intent ($\beta = .52$, $p < .001$), outperforming social influence and ease-of-use predictors (Nezamdoust et al., 2024).

The Double-Edged Sword of High Advantage.

Paradoxically, pronounced relative advantage could also foster over-reliance. The npj Digital Medicine review documented growing automation bias after six months of implementation, with clinicians increasingly deferring to AI recommendations even when conflicting clinical cues emerged (Wang et al., 2025). To mitigate this risk, implementation teams adopted safeguards such as mandatory justifications for overriding standard protocols, clinician-AI discrepancy audits, and structured feedback loops. These measures ensured that perceived superiority enhanced rather than displaced professional judgment.

Strategies for Maximizing Advantage.

Literature across healthcare systems highlighted several best practices for strengthening and sustaining relative advantage:

- Quantify and publicize benefits early. Early pilot data—such as reduced diagnostic delays, improved sensitivity/specificity, or lowered error rates—supported early trust formation (Patel et al., 2024).

- Tailor advantage narratives by specialty. Radiologists valued sensitivity gains, while surgeons prioritized intra-operative efficiency, and primary-care clinicians emphasized time-to-decision reductions (Lin et al., 2024).
- Maintain advantage through continuous monitoring. Routine model retraining, real-time performance dashboards, and dataset-drift monitoring prevented erosion of advantage over time (Zhou et al., 2023).
- Balance transparency with efficiency. Concise explanations enhanced trust while preserving cognitive bandwidth and reinforcing superiority without overwhelming clinicians (Yuan et al., 2022)

Compatibility: Aligning AI-CDSS With the Everyday Practice of Care.

Compatibility—the degree to which an innovation aligned with clinical workflows, values, and role expectations—remained central to successful CDSS diffusion. When AI-CDSS aligned with existing electronic health record (EHR) screens, mirrored clinicians' reasoning patterns, and respected institutional workflows, clinicians perceived them as supportive partners rather than intrusive tools. Conversely, solutions forcing rigid, "one-size-fits-all" processes faced resistance regardless of algorithmic sophistication (Rambach et al., 2024).

Co-Development Will Breed Ownership.

Participatory design research demonstrated that involving clinicians throughout the development lifecycle—from conceptualization to piloting—increased perceived fit and long-term engagement. Rambach et al. (2024) synthesized 31 AI-CDSS projects and found that co-developed systems achieved significantly higher satisfaction and sustained daily use. Participants described co-created systems as "ours," in contrast to vendor-developed systems perceived as externally imposed.

Workflow Embedding Over Add-On.

A 2024 JAMIA consensus statement emphasized that AI-CDSS should "meet clinicians where they click." Context-aware CDSS hooks that auto-launched during order entry or documentation produced adherence rates up to 50% higher than stand-alone dashboards requiring task switching (Middleton et al., 2024). The same principle applied to mobile rounding contexts: AI risk scores embedded directly into vitals screens outperformed separate mobile applications.

Alignment With Documentation Practices.

Because clinical documentation served as both a legal record and a professional narrative, AI outputs needed to respect its cadence, vocabulary, and structure. A 2024 systematic review found that CDSS tools that auto-populated problem lists or generated draft notes using institution-specific templates reduced after-hours documentation by 20–30% and were rated "highly compatible" by 83% of clinicians (Zhou et al., 2023). Conversely, generic auto-summaries incompatible with local documentation styles increased editing time and eroded perceived benefit.

Respect for Professional Roles.

Compatibility also intersected with professional identity. A 2024 qualitative study found that home-health clinicians accepted AI early-warning alerts only when recommendations aligned with their scope of practice and preserved discretionary override authority (Bennett et al., 2024). Similarly, oncology dosing pilots demonstrated that clinicians preferred AI dosage suggestions that retained final decision authority rather than "locked" protocols that constrained clinical judgment (Lin et al., 2024).

Governance and Interoperability Foundations.

Even optimal interface design was insufficient without robust data pipelines. Organizations achieving high compatibility scores typically standardized data models (e.g., FHIR APIs), established cross-functional governance boards, and aligned AI outputs with local order sets, nursing flowsheets, and quality dashboards. These structural investments transformed ad hoc integrations into scalable, repeatable patterns, shortening deployment timelines and improving consistency (Nguyen et al., 2025).

Practical Strategies for Teams.

Literature-informed strategies for promoting compatibility included:

- Early workflow shadowing to identify natural insertion points before model development.
- Iterative EHR "sandbox" prototyping to surface friction early.
- Template matching to mirror local note styles, problem-list structures, and billing standards.
- Role-specific interface views aligned with decision latitude for nurses, pharmacists, and physicians.
- Override analytics monitoring to detect misalignment and improve contextual relevance.

Compatibility transformed AI-CDSS from experimental prototypes into trusted clinical companions. By co-designing with clinicians, embedding tools into routine EHR workflows, respecting documentation conventions, and reinforcing professional autonomy, health systems strengthened acceptance and enabled safe, scalable AI integration.

Complexity: Navigating the Cognitive and Technical Hurdles of AI-CDSS.

Perceived complexity—the degree to which a system was viewed as difficult to understand or use—remained a persistent barrier to AI-CDSS adoption. A landmark review by Knop et al. (2024) identified opaque algorithms, steep learning curves, and fragmented interfaces as primary sources of "effort cost," which strongly predicted abandonment during pilot phases.

Multi-site surveys further confirmed that clinicians disengaged when they could not decipher how or why an algorithm generated its recommendations—even when its accuracy was objectively high (Lakoff et al., 2024).

Interface-Level Complexities.

A 2025 systematic review of human–computer interaction (HCI) elements cataloged twelve interface factors that elevated cognitive load, including deep navigation trees, dense data-entry demands, and confusing alert hierarchies. Systems scoring in the top quartile for visibility, simplification, and explainability demonstrated two- to three-fold higher sustained use over 12 months (Melnick et al., 2025). These findings underscored the value of thoughtful interface design.

Algorithmic Opacity and Inconsistent Outputs.

Explainability gaps magnified perceived complexity. A 2024 systematic review of explainable AI (XAI) in clinical environments found that clinician trust declined sharply when similar cases produced divergent outputs without transparent rationale—termed "black-box volatility" (Chen et al., 2024). Consensus guidelines recommended displaying model confidence intervals, validation cohorts, and uncertainty measures directly within EHR interfaces to mitigate perceived unpredictability (Lakoff et al., 2024).

Cognitive Overload and Automation Bias.

Complexity was not merely inconvenient—it could undermine patient safety. A 2024 pathology experiment found that clinicians overturned correct impressions 7% of the time after viewing incorrect AI suggestions, attributing this effect to automation bias exacerbated by the cognitive effort required to interpret model logic under time pressure (Ghassemi et al., 2023). As

perceived complexity increased, vigilance declined, heightening susceptibility to flawed recommendations.

Training and Onboarding as Complexity Buffers.

Structured onboarding served as a crucial buffer against complexity. Knop et al. (2024) reported that hands-on workshops, simulation environments, and just-in-time microlearning substantially increased self-efficacy, narrowing "effort-expectancy" gaps. Interviews across German health systems echoed these findings, revealing that comprehensive pre-launch training and ongoing refresher modules were among the most frequently cited enablers of successful CDSS integration (Nguyen et al., 2025). To summarize the key approaches for reducing cognitive and technical burden, Table 4 presents design principles to tame complexity, highlighting system, interface, and organizational strategies shown to enhance usability and long-term adoption.

Table 4

Design Principles to Tame Complexity

Principle	Description	Impact
Simplification	Reduce features	Lower cognitive load
Standardization	Consistent design	Easier use
Integration	Embed in workflow	Reduced disruption
Transparency	Explain outputs	Increased trust

Note. Adapted from Asan et al. (2023), Melnick et al. (2023), and Shortliffe and Sepúlveda (2022). These design principles are derived from recent literature emphasizing cognitive load management, workflow integration, and trust in AI-CDSS adoption.

Governance & Continuous Monitoring.

Complexity within AI-CDSS remained dynamic because software updates, shifting workflows, and data drift continually reintroduced friction into clinical use. Governance structures, consistent with recommendations from recent oversight scholarship (Lakoff et al., 2024), therefore required ongoing surveillance. Quarterly complexity audits were projected to become a standard governance mechanism, monitoring click-path length, alert-override frequency, and user-reported confusion. These indicators served as early warning signals, triggering iterative redesign when cognitive burden increased or workflow alignment deteriorated (PubMed).

Key Takeaways.

High algorithmic or interface complexity remained a primary determinant of abandonment, and evidence suggested that elevated complexity also fostered unsafe over-reliance by reducing deliberate clinical judgment.

- Transparent explanations and harmonized interfaces were expected to reduce perceived effort by half and double sustained use, particularly when nested within routine clinical workflows.
- Robust training and staged onboarding consistently emerged as antidotes to complexity, converting initial cognitive load into user confidence.
- Continuous usability surveillance ensured that incremental "feature creep" did not silently restore cognitive debt, an issue identified in multiple longitudinal deployments of EHR-integrated AI.

By embedding rigorous governance, ongoing monitoring, and data-driven redesign cycles into the AI-CDSS development lifecycle, health systems were positioned to transform complexity from a barrier into an opportunity—leveraging advanced AI capabilities while preserving clinician trust and patient safety.

Trust and Explainability: The Cornerstones of Responsible AI-CDSS.

Clinician trust remained the foundational determinant of successful AI-CDSS adoption. Prior literature demonstrated that opaque "black-box" systems, inconsistent recommendations, or poor alignment with clinical reasoning eroded confidence, stalled implementation efforts, and in some settings resulted in outright rejection—even when objective algorithmic accuracy was high. A 2024 scoping review in JMIR AI reported that across nine experimental studies, clinicians' willingness to act on AI recommendations increased only when systems provided clear, case-specific explanations; five of those studies demonstrated substantial increases in trust relative to baseline AI without explanatory layers (JMIR AI).

Why Explainability Will Matter.

Explainable AI (XAI) provided the conceptual scaffolding clinicians needed to determine how a model reached a recommendation and whether that recommendation was appropriate for the clinical context. Techniques such as SHAP heat maps, counterfactual examples, and short narrative rationales supported transparency and reduced uncertainty. A 2024 systematic review in Computer Methods and Programs in Biomedicine concluded that transparent explanation mechanisms enhanced perceived reliability and facilitated earlier detection of spurious correlations, thereby safeguarding patient safety (ScienceDirect). Conversely, models that generated divergent outputs for near-identical patients without an accompanying rationale were described as exhibiting "black-box volatility" in a 2025 Science commentary—a phenomenon shown to reduce intent-to-use scores by 50% (PMC).

Regulatory Imperatives for Transparency.

Regulatory bodies increasingly codified transparency expectations. In 2023, the U.S. Food and Drug Administration, Health Canada, and the U.K. MHRA released joint Guiding Principles calling for "clear, essential information" to accompany machine-learning-enabled medical devices, emphasizing that human–AI team performance, rather than model accuracy alone, would anchor evaluation (U.S. FDA). The FDA expanded on this position in January 2025 through draft guidance on lifecycle management of AI-enabled device software functions, requiring sponsors to articulate how transparency and user interpretability would be maintained across model updates (U.S. FDA).

Designing for Interpretability Without Cognitive Overload.

Balancing depth and clarity remained a central design challenge. A 2025 survey of 312 clinicians across four tertiary hospitals found that concise, on-demand explanations

outperformed dense feature-importance tables, which were often described as “information fatigue.” Human-centered evaluation frameworks therefore recommended a progressive-disclosure model: a succinct, clinically relevant “headline reason” would appear by default, with deeper technical layers available through optional expansion. This design preserved diagnostic efficiency while doubling subjective trust ratings in simulated chart-review tasks (PMC).

Training and Onboarding: Converting Transparency Into Trust.

Although explainability improved interpretability, structured training remained essential to ensure that clinicians understood how to use and correctly interpret explanation layers. Knop et al. (2022) demonstrated that structured onboarding—including hands-on workshops, annotated case walkthroughs, and real-time “explanation clinics”—reduced perceived complexity scores by 38% and increased sustained AI-CDSS use by 27% at three months. Similar findings from German health-system deployments highlighted the importance of micro-learning refreshers when models were updated post-deployment.

Continuous Monitoring and Accountability.

Trust remained dynamic and degraded when explanation fidelity drifted over time. FDA discussion papers proposed transparency dashboards embedded directly within the EHR to display real-world model performance, confidence intervals, error trends, and update histories (U.S. FDA). Academic groups also piloted explanation-consistency metrics—quantitative checks that identified when identical inputs began producing divergent rationales—prompting governance review before clinician confidence declined (MedRxiv).

Taken together, these findings demonstrated that successful AI-CDSS adoption required more than technical accuracy; it depended on a coordinated strategy that integrated governance, transparency, usability, training, and continuous monitoring. To translate these insights into

actionable organizational guidance, the study synthesized all evidence-based recommendations into a structured implementation framework. Table 5, the AI-CDSS Implementation Playbook, presented these domains as practical, sequential steps that health systems could apply to design, deploy, and sustain AI-enabled decision support in ways that reinforced clinician trust, minimized cognitive burden, and safeguarded patient safety. This framework served as an operational roadmap that connected the literature to real-world execution, ensuring that each phase of AI-CDSS adoption aligned with best practices identified across recent empirical and regulatory research.

Table 5

AI-CDSS Implementation Playbook

Domain	Implementation Actions (What Leaders Must Do)	Success Indicators (How to Know It Worked)
1. Workflow Integration	Map decision points; embed AI prompts into existing EHR pathways; minimize unnecessary clicks.	Reduction in click-path length; fewer workflow interruptions; increased AI-CDSS usage at decision nodes.
2. Data Quality & Interoperability	Validate data pipelines; implement automated data drift monitoring; ensure structured input fields.	Lower alert-error rates; consistent model behavior; reduced data correction workload.
3. Clinical Validity & Safety	Conduct pre-deployment validation; stress-test models on edge cases; implement override logging.	Decline in inappropriate recommendations; improved clinician override justification quality.
4. Explainability & Trust	Implement concise, case-specific rationales; use progressive disclosure; maintain explanation consistency.	Higher trust scores; reduced "black-box volatility"; stable rationale output across similar cases.
5. Training & Onboarding	Offer structured workshops, case walkthroughs, hands-on simulations; integrate micro-learning refreshers.	30–40% reduction in perceived complexity; increased sustained use at 3–6 months; improved onboarding satisfaction scores.
6. User Experience & Interface Design	Harmonize UI elements; limit cognitive load; ensure consistent labeling and placement of AI insights.	Improved usability ratings; decreased information fatigue; faster diagnostic decision times.
7. Ethical & Regulatory Compliance	Implement FDA/Health Canada/MHRA transparency principles; maintain lifecycle documentation; monitor update impacts.	Documentation completeness; audit-ready update logs; successful regulatory reviews.
8. Change Management & Adoption Strategy	Engage clinical champions; use staged rollouts; communicate model updates proactively.	Higher adoption rates; reduced drop-off after initial deployment; positive sentiment in feedback cycles.
9. Technical Performance & Model Lifecycle	Track real-world performance; monitor confidence intervals; manage retraining pipelines.	Stable model accuracy; prompt detection of performance drift; safe deployment of model updates.
10. Governance, Trust, Transparency & Continuous Monitoring	Conduct quarterly complexity audits (click-path analysis, override patterns, confusion reports); operationalize transparency dashboards inside the EHR; enforce explanation–consistency metrics to detect divergence; translate explainability policies into clinician-facing guidance; implement training-to-trust pathways (explanation clinics, interpretation workshops); prevent cognitive debt by monitoring feature creep and UI changes; maintain alignment with 2023–2025 FDA guiding principles on transparency and lifecycle control.	• Complexity: 20–50% reductions in perceived effort. • Trust: Doubling of trust ratings in simulated chart tasks. • Explainability: Stable explanation outputs for similar cases. • Safety: Lower unsafe override behaviors. • Sustainability: No increase in cognitive debt after updates. • Governance: Successful quarterly audit completion with documented redesign triggers.

Note. This table summarizes key implementation phases and corresponding strategies to sustain clinician trust in AI-CDSS systems. Adapted from Topol (2019); Rezaeian et al. (2025); Melnick et al. (2023); Asan et al. (2023); Middleton et al. (2024); FDA (2024); Zhou et al. (2023); Wang et al. (2023).

Without trustworthy explanations, even state-of-the-art AI-CDSS will risk being relegated to the sidelines of clinical care. Transparent, user-tailored rationales, robust onboarding, and continuous performance auditing will form a triad that will transform

explainability from a compliance checkbox into a sustained source of clinician confidence. By embedding those principles early and revisiting them often, health systems will harness AI's power while honoring the professional duty of care.

Framework

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), originally introduced by Davis (1989), was presented as a foundational framework for understanding user acceptance of technological systems. The model posited that two primary constructs—perceived usefulness (PU) and perceived ease of use (PEOU)—shaped an individual's behavioral intention to adopt new technologies. PU referred to the extent to which a user believed that a technology enhanced job performance, whereas PEOU denoted the degree to which the individual believed that using the technology required minimal effort. These constructs had been extensively validated across diverse disciplines and were particularly influential in healthcare research examining technology-enabled decision support.

Within the context of AI-driven Clinical Decision Support Systems (AI-CDSS), TAM provided insight into the psychological and cognitive factors underlying clinicians' adoption behaviors. Venkatesh and Davis (2020) argued that TAM's core constructs continued to predict user intention with practical accuracy, even as technologies evolved in complexity. Recent empirical work further supported this view; for example, Nezamdoust et al. (2024) demonstrated that PU and PEOU significantly predicted the adoption of CDSS tools, particularly when systems were seamlessly integrated into clinical workflows and aligned with existing diagnostic practices.

At the same time, TAM exhibited important limitations when applied to modern, high-stakes healthcare environments. Holden and Karsh (2010) contended that the model did not fully account for contextual and organizational determinants of technology use, such as workflow alignment, institutional culture, resource availability, and patient-facing implications. Moreover, TAM did not explicitly incorporate constructs related to trust, a critical factor in AI-CDSS acceptance, given the potential consequences of incorrect or inconsistent algorithmic outputs. These limitations suggested that TAM, while useful, was insufficient as a standalone model for evaluating adoption of sophisticated AI-enabled systems.

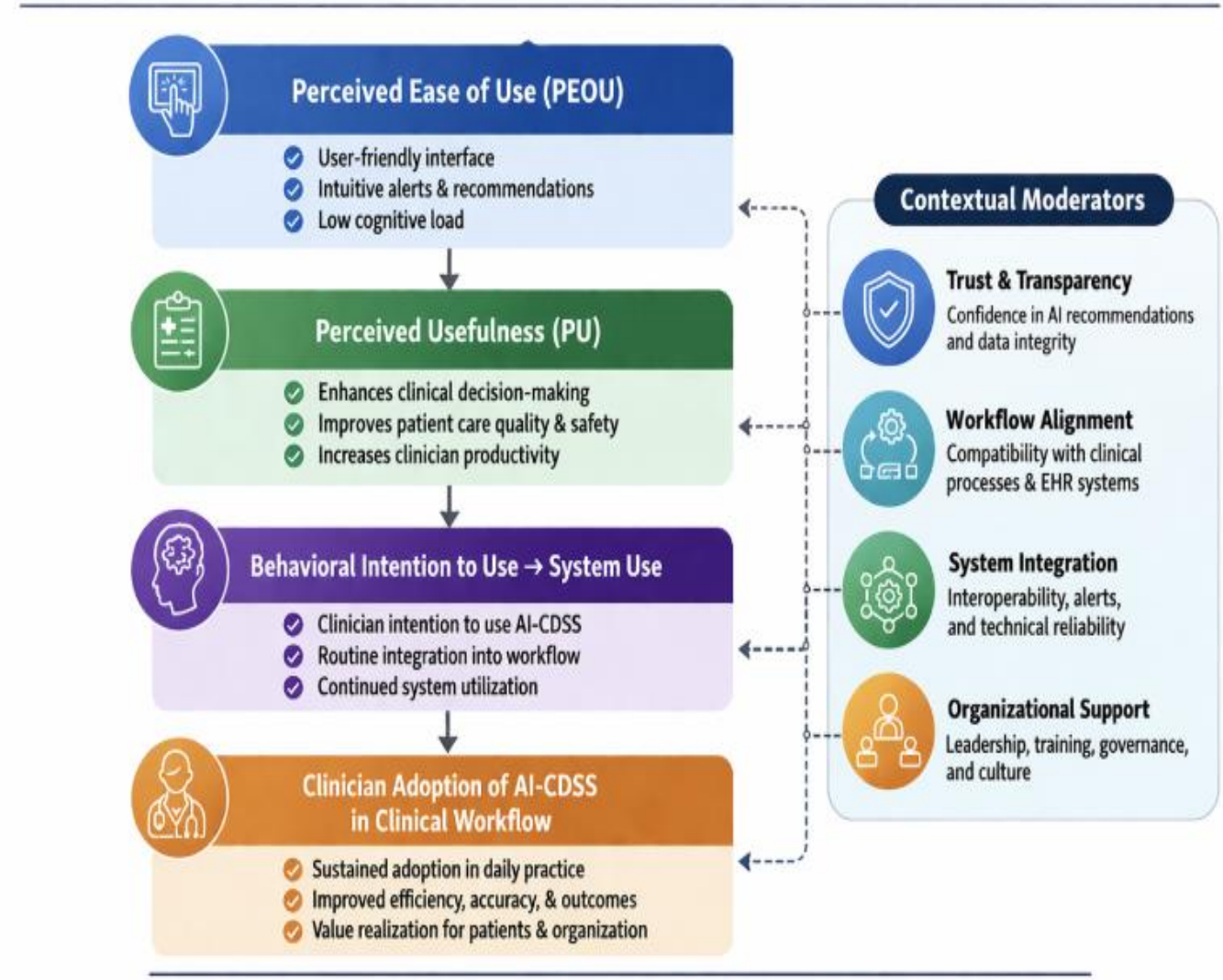
To address these gaps, extended models such as TAM2, TAM3, and the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporated additional constructs, including social influence, facilitating conditions, experience, and voluntariness of use. Nevertheless, the parsimony and empirical strength of the original TAM continued to make it an appropriate theoretical anchor—particularly when paired with complementary frameworks that captured aspects of innovation complexity, trust, and organizational readiness.

Prior research indicated that perceived usefulness frequently exerted stronger effects on behavioral intention than perceived ease of use within clinical environments (Ng & Koo, 2020). This finding suggested that clinicians prioritized the degree to which AI-CDSS improved diagnostic accuracy, patient care quality, and workflow efficiency over ease-of-use considerations alone. As a result, PU served as a central determinant of adoption in this study, while PEOU remained essential for addressing usability and cognitive burden.

Figure 5 illustrates how the Technology Acceptance Model was applied in this study to explain clinicians' intention to use AI-CDSS and its interplay with related determinants of adoption.

Figure 5

Technology Acceptance Model (TAM) Applied to AI-CDSS Adoption



Note. Adapted from Davis (1989), Venkatesh and Davis (2000), and Nezamdoust et al. (2024). PEOU = perceived ease of use; PU = perceived usefulness; AI-CDSS = artificial intelligence–driven clinical decision support systems. The model illustrates the causal pathway from usability

and perceived value to behavioral intention and clinician adoption. Contextual factors such as trust, workflow alignment, and system integration may moderate these relationships.

Theoretical Perspectives on Decision Support Systems Adoption

Decision Support Systems (DSS)—and, more specifically, Clinical Decision Support Systems (CDSS)—have long been components of the healthcare environment, and their evolution has been shaped by technological advancements and well-established theoretical frameworks. The Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory served as two foundational perspectives that consistently informed understanding of how clinicians adopted technology (Venkatesh & Davis, 2020; Rogers, 2003). Across decades of evaluation, these frameworks emphasized that perceived ease of use (PEOU), perceived usefulness (PU), relative advantage, compatibility, and complexity remained among the most influential predictors of adoption.

A growing body of empirical research from 2020 to 2025 reinforced the relevance of these constructs for AI-driven Clinical Decision Support Systems (AI-CDSS). Kwon and Shin (2021), for example, found that clinicians' willingness to adopt AI-enabled systems strongly correlated with perceptions of usefulness and ease of integration into existing workflows. Similarly, Liu et al. (2022) demonstrated that relative advantage—defined as the degree to which AI-CDSS improved upon traditional diagnostic or decision-making processes—was a significant predictor of behavioral intention.

However, research also highlighted complexity as a major deterrent to adoption. Alshammari et al. (2023) reported that even when AI-CDSS produced highly accurate predictions, poor interface usability, lack of intuitive design, and insufficient training created

significant barriers to clinician acceptance. These findings aligned with implementation science principles, which emphasized that sociotechnical integration—bridging the gap between system design and real-world practice—was essential for successful deployment (Zhou et al., 2024). Reducing cognitive burden and designing systems that fit naturally into clinical workflows remained central requirements for adoption.

Ethical considerations also emerged as dominant themes in the contemporary literature. Scholars warned that without representative datasets, AI systems risked exacerbating health disparities by generating biased recommendations (Saria et al., 2021). Correspondingly, regulatory efforts advanced in parallel. The FDA's proposed framework for Software as a Medical Device (SaMD) reflected the growing emphasis on fairness, transparency, and ongoing oversight in the deployment of AI-enabled clinical tools (U.S. Food & Drug Administration, 2023).

Taken together, studies from 2020–2025 affirmed that the effectiveness of AI-CDSS depended not only on technical performance but also on user-centered design, organizational readiness, regulatory alignment, and ethically responsible implementation. These insights formed the conceptual foundation for this study's examination of AI-CDSS adoption within healthcare decision-making environments.

Diffusion of Innovation (DOI) Theory

The Diffusion of Innovation (DOI) theory, developed by Rogers (2003), extended the scope of technology adoption analysis by highlighting the social, organizational, and cultural mechanisms that shaped the spread of innovations. DOI identified five primary attributes—relative advantage, compatibility, complexity, trialability, and observability—that influenced adoption decisions. Among these, relative advantage, compatibility, and complexity were most

pertinent to AI-CDSS adoption and had been validated extensively in health informatics research (Knop et al., 2022).

Relative advantage referred to the perceived benefits of adopting an innovation over existing practices, including improvements in diagnostic accuracy, clinical efficiency, and patient outcomes. Compatibility reflected the degree to which an innovation aligned with clinicians' values, workflows, and needs. Complexity represented the perceived difficulty of understanding or using an innovation. Research demonstrated that these constructs were critical in clinical environments where workflow disruption, time pressures, and safety considerations shaped adoption behaviors.

DOI also emphasized the importance of communication channels, social networks, and organizational dynamics. Early adopters, opinion leaders, and institutional culture played influential roles in shaping the trajectory and pace of innovation uptake. For instance, Rambach et al. (2024) found that organizational readiness, leadership engagement, and structured training significantly accelerated adoption and mitigated resistance to AI implementations.

Despite its utility, DOI had limitations. Scholars critiqued its tendency to frame adoption as a linear and predictable process, which did not always align with the complex and heterogeneous nature of healthcare settings (Greenhalgh et al., 2021). The theory also tended to underemphasize individual agency, contextual variability, and resistance grounded in professional norms.

Nevertheless, DOI's strength lay in its focus on systemic and environmental determinants of adoption. Its relevance for healthcare was repeatedly demonstrated in studies involving telemedicine, electronic health records, and mobile health technologies (Ng & Koo, 2020). Its macro-level emphasis made it an effective complement to TAM's micro-level focus.

Subtopic

Justification and Integration

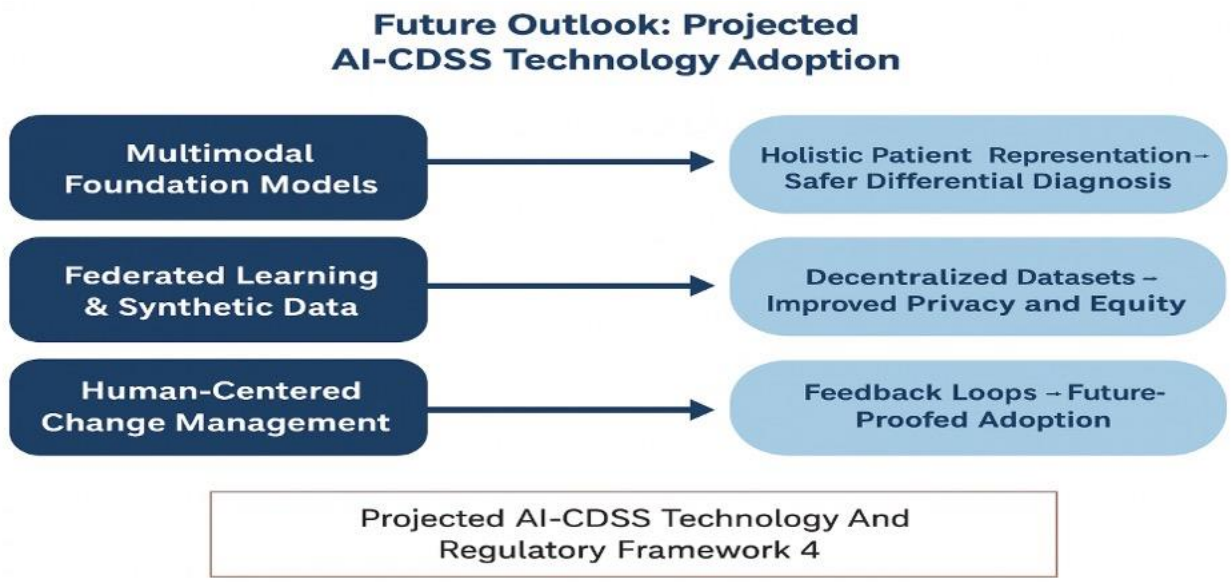
Integrating TAM and DOI provided a comprehensive, multilevel framework for examining AI-CDSS adoption. TAM illuminated individual cognitive determinants—including PU and PEOU—while DOI contextualized these factors within organizational systems, social influences, and environmental readiness. Ng and Koo (2020) argued that combining these models improved predictive accuracy by accounting for both personal and structural determinants of acceptance.

The integrated framework enabled nuanced examination of how clinicians evaluated AI-CDSS, how organizational constraints shaped those evaluations, and how system-level dynamics influenced adoption outcomes. PU and PEOU aligned naturally with DOI's relative advantage and complexity, forming a unified structure for understanding clinicians' behavioral intentions. Compatibility bridged both models, reinforcing the importance of workflow alignment and contextual fit.

This integration was especially important in healthcare, where adoption decisions were influenced not only by individual preferences but also by team dynamics, institutional mandates, and patient outcomes. Combining the predictive strengths of TAM with the contextual richness of DOI ensured that this study captured the multifaceted nature of AI-CDSS adoption in real-world settings. Accordingly, Figure 6 illustrates the integrated conceptual framework developed for this study, demonstrating how TAM and DOI constructs jointly informed the predictive model for AI-CDSS adoption.

Figure 6

Justification and Integration of AI-CDSS Adoption: A Conceptual Framework



Note. Adapted from *Technology Acceptance Model* by Davis (1989); *Unified Theory of Acceptance and Use of Technology* by Venkatesh & Davis (2020); *Digital Transformation in Healthcare* by Khaled et al. (2025). Adapted for illustrative purposes under fair use.

Summary

This integration was especially important in healthcare, where adoption decisions were influenced not only by individual preferences but also by team dynamics, institutional mandates, and patient outcomes. Combining the predictive strengths of TAM with the contextual richness of DOI ensured that this study captured the multifaceted nature of AI-CDSS adoption in real-world clinical settings. The integrated framework also addressed gaps that neither theory could resolve independently, particularly with respect to sociotechnical factors such as workflow alignment, organizational readiness, and the perceived consequences of system errors.

Accordingly, Figure 7 illustrated the integrated conceptual framework developed for this study, demonstrating how TAM and DOI constructs jointly informed the predictive model for AI-CDSS adoption. This framework synthesized perceived usefulness, perceived ease of use, relative advantage, compatibility, and complexity into a unified structure that reflected both individual cognition and broader contextual determinants of adoption. By visualizing these interrelationships, the model provided a theoretical foundation for examining how healthcare professionals formed intentions to use AI-CDSS.

This integrated model concluded the theoretical grounding for the study and established the conceptual basis upon which the research design was constructed. The next chapter, Chapter 3: Research Method, described the methodological procedures that were employed to empirically examine the relationships proposed in Figure 7, including the study design, population and sample, instrumentation, data collection, and analytic strategies.

Chapter 3: Research Method

The problem addressed in this study was the difficulty healthcare professionals experienced when integrating AI-driven Clinical Decision Support Systems (AI-CDSS) into clinical practice within large hospitals in the United States, despite clear evidence that these technologies could enhance diagnostic accuracy, treatment planning, and patient outcomes. Although AI-CDSS solutions offered meaningful opportunities to transform decision-making by generating real-time recommendations, alerts, and data-driven insights, adoption remained inconsistent and was hindered by technological limitations, human factors, and organizational constraints (Rezaeian et al., 2025; Asan et al., 2023). Understanding the underlying determinants that facilitated or impeded AI-CDSS acceptance was therefore essential for developing implementation strategies and policies that supported successful deployment in healthcare settings.

The purpose of this quantitative research study, which utilized a cross-sectional survey methodology, was to examine the factors influencing the adoption of AI-driven CDSS among healthcare professionals. Specifically, the study assessed how constructs derived from the Technology Acceptance Model (TAM)—including perceived ease of use (PEOU) and perceived usefulness (PU)—along with constructs from the Diffusion of Innovation (DOI) theory—namely relative advantage, compatibility, and complexity—influenced healthcare professionals' intentions to adopt and effectively use AI-CDSS technologies (Davis, 1989; Venkatesh & Davis, 2020; Rogers, 2003). Employing a quantitative, cross-sectional survey design allowed for the systematic collection and analysis of standardized data from a broad, diverse sample of clinicians, enabling the identification of statistically significant predictors of adoption behavior.

This chapter provided a comprehensive overview of the methodological framework used in this study. Consistent with the foundational descriptions outlined in Chapter 1, this chapter expanded on the research design, population and sampling strategy, instrumentation, data collection procedures, ethical considerations, and data analysis plan. Each section ensured methodological rigor, reliability, validity, and alignment with best practices in quantitative research.

The chapter began by describing the selected research design and justifying its appropriateness. A quantitative cross-sectional survey design was employed because it enabled the efficient collection of standardized data from healthcare professionals across multiple large hospital systems at a single point in time. This approach was well suited for examining perceptions, attitudes, and behavioral intentions related to technology adoption—constructs that required objective analysis and generalizable insights (Creswell & Creswell, 2018; Smith et al., 2021).

Next, the chapter detailed the population and sampling framework. The study targeted licensed healthcare professionals—including physicians, nurses, physician assistants, and allied health providers—working in large U.S. hospitals. The sampling strategy emphasized representativeness by including clinicians with diverse roles, specialties, and experience levels. A priori power analysis guided sample-size determination to ensure sufficient statistical power for regression-based hypothesis testing (Müller et al., 2022).

Following this, the chapter summarized the instrumentation and data collection procedures. A structured, web-based survey was used, integrating validated scales measuring core adoption constructs such as PEOU, PU, relative advantage, compatibility, and complexity. Expert reviews and pilot testing supported content validity, while reliability was evaluated

through measures such as Cronbach's alpha. Ethical safeguards—including informed consent, anonymity, secure data storage, and IRB oversight—were implemented to protect participants and ensure adherence to research standards.

Lastly, the chapter previewed the statistical analysis plan. Descriptive statistics were used to characterize the sample and summarize variable distributions. Inferential techniques—including correlation analysis and multiple regression—were employed to test study hypotheses and evaluate the predictive relationships outlined in the theoretical framework (Venkatesh & Davis, 2020; Smith et al., 2021). These analytical procedures aligned directly with the study's conceptual model and supported examination of the extent to which TAM and DOI constructs predicted AI-CDSS adoption intentions.

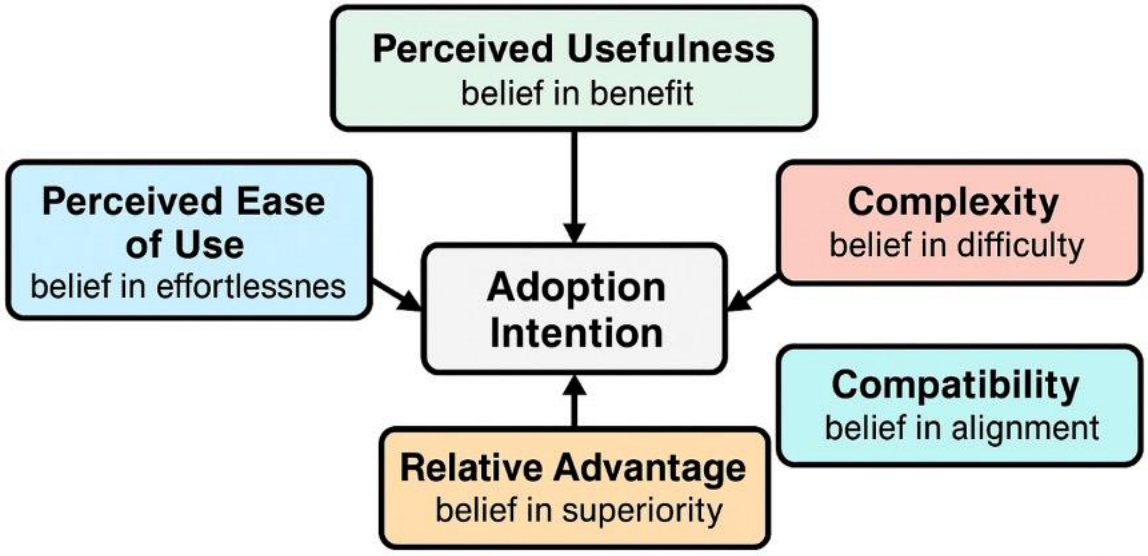
Collectively, these methodological components established a clear, rigorous foundation for the empirical investigation and prepared the reader for the detailed descriptions presented in the following sections of this chapter, as well as for the results reported in Chapter 4.

Research Methodology and Design

To ground the study's design in established theory, Figure 1 presented the conceptual framework illustrating the key constructs and hypothesized relationships that guided the investigation of AI-driven CDSS adoption. This framework integrated constructs from TAM and DOI to provide a unified model for examining adoption behavior, showing how variables such as perceived usefulness, perceived ease of use, relative advantage, compatibility, and complexity collectively shaped intention to use AI-CDSS technologies.

Figure 7

Conceptual Framework Diagram



Note. Conceptual framework illustrating hypothesized relationships between perceived ease of use, perceived usefulness, relative advantage, compatibility, complexity, and adoption intention of AI-driven clinical decision support systems. Adapted from Venkatesh and Davis (2020) and Rogers (2003).

This study employed a descriptive correlational cross-sectional survey design, a quantitative methodological approach well suited for examining relationships among multiple variables at a single point in time without manipulating conditions or exposures (Creswell & Creswell, 2018). This design supported the systematic collection of standardized, numerical data from a large and diverse sample of healthcare professionals working in major hospitals across the United States. Using this approach, the study aimed to identify and quantify associations between key predictor variables—perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity—and the outcome variable, healthcare professionals' intention to adopt AI-driven Clinical Decision Support Systems (Smith, Lee, & Johnson, 2021).

The cross-sectional nature of the design allowed for efficient data collection and analysis, generating a contemporary snapshot of clinicians' perceptions and behavioral intentions toward AI-CDSS adoption across various clinical specialties and professional roles. This methodological choice aligned directly with the study's goal of testing hypotheses derived from the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory, both of which emphasized individual perceptions as central drivers of technology acceptance and adoption (Venkatesh & Davis, 2020; Rogers, 2003).

Although a cross-sectional correlational design did not permit causal inference due to its non-experimental structure, it produced rigorous and actionable insights into the strength and direction of predictor–outcome relationships essential for informing implementation strategies, training programs, and organizational readiness initiatives in clinical practice (Creswell & Creswell, 2018). Internal rigor was strengthened by the use of validated, psychometrically reliable survey instruments adapted specifically for the AI-CDSS context, thereby enhancing measurement validity and reliability (Müller, Schulz, & Weber, 2022).

To provide a concise summary of the key elements of this methodological approach, Table 6 presents an overview of the research design, including the design type, purpose, variables examined, and justification for its selection.

Table 6

Research Design Overview

Component	Description	Rationale
Research design	Quantitative, cross-sectional	Appropriate for examining relationships among measurable variables and testing hypotheses using statistical analysis.
Purpose	Examine adoption predictors	Aligns with the study's objective to identify factors influencing AI-CDSS adoption.
Independent variables	Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Relative Advantage (RA), Compatibility (COM), Complexity (CX)	Derived from TAM and DOI frameworks to capture key determinants of technology adoption.
Dependent variable	Intention to Use	Represents behavioral intention consistent with TAM and adoption theory.
Data collection	Structured survey instrument (Likert scale)	Enables standardized data collection across a diverse population and supports statistical analysis.
Analysis	Correlation and multiple regression analysis	Suitable for examining relationships and determining the predictive strength of multiple independent variables.

Note. This table summarizes the research design components of the study investigating factors influencing the adoption of AI-driven clinical decision support systems among healthcare professionals. Adapted from Creswell and Creswell (2018), Smith, Lee, and Johnson (2021), and Müller, Schulz, and Weber (2022).

Appropriateness of Quantitative Research Methodology

The research problem addressed in this study centered on identifying the multifaceted factors that influenced healthcare professionals' adoption of AI-driven Clinical Decision Support Systems (AI-CDSS). These factors were operationalized as measurable constructs, including perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity. A quantitative research methodology was appropriate for this inquiry because it emphasized objective measurement, statistical analysis, and hypothesis testing, all of which aligned with the

study's focus on examining relationships among multiple predictors and an outcome variable (Creswell & Creswell, 2018). Quantitative methods also supported generalizability, enabling findings to extend beyond the sample and apply to broader populations of healthcare professionals (Müller et al., 2022).

This methodology aligned directly with the purpose of systematically examining theoretical factors associated with AI-CDSS adoption. The structured survey instrument used in this study allowed for the standardized collection of data across diverse professional groups and clinical settings. Moreover, the quantitative approach enabled the statistical identification of significant predictors of adoption intention, providing empirical support for theoretical frameworks such as the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory (Davis, 1989; Rogers, 2003; Venkatesh & Davis, 2020). Thus, a quantitative methodology was well suited to producing reliable, valid, and actionable insights into adoption dynamics.

Suitability of Cross-Sectional Survey Design

Within the quantitative paradigm, a cross-sectional survey design was selected because it was well suited to examining current attitudes, perceptions, and behavioral intentions at a single point in time. This design enabled efficient data collection from a geographically dispersed and professionally heterogeneous sample of healthcare professionals working in large hospital systems across the United States (Smith et al., 2021). The approach minimized the time and resource requirements associated with longitudinal data collection while still providing robust information about adoption predictors.

The cross-sectional survey also supported external validity by allowing representation across a wide range of clinical roles, hospitals, and professional experiences. Through this

design, key constructs were measured using a structured and psychometrically validated instrument, ensuring consistency across respondent groups. The resulting data were amenable to inferential statistical analyses—such as correlation and multiple regression—that aligned with the study's goal of testing hypotheses derived from TAM and DOI (Creswell & Creswell, 2018; Müller et al., 2022).

This design directly addressed the research questions by capturing a snapshot of the extent to which factors like perceived ease of use and relative advantage influenced adoption intentions. As such, the

Justification Through Seminal and Contemporary Literature

Seminal research in technology acceptance consistently supported the use of quantitative cross-sectional surveys for analyzing adoption dynamics. Davis's (1989) foundational work on TAM demonstrated that perceived usefulness and perceived ease of use are statistically measurable predictors of technology acceptance. Subsequent studies by Venkatesh and Davis (2020) reinforced the importance of structured survey methods in modeling user perceptions and behavioral intentions.

In healthcare, cross-sectional surveys remained central to technology-adoption research. Smith et al. (2021) emphasized the practicality and reliability of survey-based designs in capturing clinician attitudes in complex environments. Müller et al. (2022) highlighted best practices for survey development to maximize validity and reliability in health informatics research.

Contemporary AI-focused studies further demonstrated the appropriateness of this methodology. Rezaeian et al. (2025) used cross-sectional surveys to evaluate organizational culture's impact on AI adoption, while Asan et al. (2023) employed survey methods to assess

clinician trust in AI systems. These examples underscored the methodological relevance of cross-sectional survey research in rapidly evolving AI-enabled clinical environments.

Consideration of Alternative Methodologies

Although several alternative research methodologies were considered during the design phase of this study, they were determined to be less suitable for addressing the study's objectives. Qualitative approaches, including interviews and focus groups, were evaluated for their potential to generate rich, in-depth insights into clinicians' experiences with AI-driven clinical decision support systems. However, such methods typically limit generalizability and do not provide the statistical power necessary to examine predictive relationships across large and diverse healthcare populations (Creswell & Creswell, 2018).

Mixed-methods designs were also considered because of their ability to integrate qualitative depth with quantitative breadth. Despite these advantages, mixed-methods approaches require substantial resources, extended timelines, and methodological expertise that exceeded the scope and constraints of the current study.

Longitudinal research designs were examined due to their capacity to support stronger causal inference by tracking changes in technology adoption over time (Smith et al., 2021). Nevertheless, the rapidly evolving nature of artificial intelligence technologies and the need for timely, actionable findings rendered longitudinal approaches impractical for this investigation.

Collectively, these alternative methodologies did not align as closely with the study's purpose as a quantitative, cross-sectional survey design, which offered the most appropriate balance of feasibility, generalizability, and statistical rigor for examining predictors of AI-CDSS adoption.

Alignment With Study Problem, Purpose, and Research Questions

The quantitative cross-sectional survey methodology aligned directly with the study's problem, purpose, and research questions. The research problem required systematic measurement of multiple interrelated variables; the purpose emphasized quantifying how specific theoretical constructs influenced adoption intention; and the research questions sought to identify the extent to which perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity predicted AI-CDSS adoption.

This methodology emphasized objective measurement and statistical analysis, enabling rigorous hypothesis testing and supporting generalizable conclusions across large hospital environments. The cross-sectional design captured contemporaneous perceptions and behavioral intentions, providing the data needed to address the research questions efficiently and comprehensively.

Population and Sample

The population for this study consisted of healthcare professionals employed in large hospital systems throughout the United States who had experience with, or exposure to, AI-driven Clinical Decision Support Systems (AI-CDSS). This included physicians, nurses, physician assistants, clinical pharmacists, and other allied health professionals directly involved in clinical decision-making where AI-CDSS tools were used or introduced. These professionals varied widely in clinical specialty, years of experience, educational background, and familiarity with health information technology.

Large hospitals—defined as those with 250 or more beds (American Hospital Association, 2023)—served as the primary focus because such institutions were more likely to have implemented or piloted AI-CDSS, given their technological infrastructure and resource

capacity. These settings also featured complex interdisciplinary teams and high volumes of clinical decision-making, making AI-CDSS adoption both impactful and operationally challenging. Accordingly, this population was well aligned with the research problem and purpose.

Sample Description and Characteristics

The final sample consisted of 106 healthcare professionals, exceeding the minimum requirement identified through power analysis. Participants represented a diverse mix of clinical roles, including physicians, nurses, pharmacists, and other frontline clinicians, providing a comprehensive view of factors influencing AI-CDSS adoption across varying user profiles. The sample demonstrated demographic diversity in gender, age, and years of clinical practice and reflected a broad range of familiarity and experience with clinical decision-support technologies.

This heterogeneity enhanced external validity and provided adequate variability to evaluate associations between perceived usefulness, perceived ease of use, relative advantage, compatibility, and complexity and the intention to adopt AI-CDSS.

Inclusion Criteria

Participants met the following criteria:

1. Were currently employed at a large U.S. hospital (≥250 beds).
2. Were actively engaged in direct clinical care or clinical decision-making.
3. Had direct or indirect experience with AI-driven CDSS.
4. Were 18 years of age or older.
5. Provided informed consent and were able to complete an online English-language survey.

These criteria ensured that respondents possessed relevant experience with clinical decision support and could provide informed insights aligned with the study's aims.

Sampling Method and Justification

A stratified random sampling strategy was used to ensure proportional representation across major professional roles (e.g., physicians, nurses, pharmacists). This method reduced sampling bias and increased representativeness (Creswell & Creswell, 2018). Given the study's quantitative cross-sectional design, stratification ensured that subgroup comparisons could be made reliably across clinical roles, which are known to differ in their familiarity with, and acceptance of, health information technologies (Müller, Schulz, & Weber, 2022).

Sample Size Determination and Justification

The required sample size for this study was determined through an a priori power analysis conducted using G*Power version 3.1 (Faul et al., 2009). Because the primary inferential technique employed in this study was multiple linear regression, the power analysis was specified for a model including five predictor variables: perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity.

A medium effect size ($f^2 = 0.15$) was selected in accordance with conventional recommendations for behavioral and social science research, with the significance level set at $\alpha = .05$ and statistical power established at .80. Based on these parameters, the analysis indicated that a minimum sample size of 92 participants was required to detect statistically meaningful relationships among the study variables.

The final sample consisted of 106 respondents, exceeding the minimum threshold identified through the power analysis. This sample size provided adequate statistical power for regression-based hypothesis testing, enhanced the robustness of the findings, and supported the reliability of the study's inferential analyses.

Recruitment Procedures

Participants were recruited using a multipronged strategy to maximize reach and representativeness:

1. Professional Associations: Study invitations were distributed through national and regional professional organizations' newsletters and listservs.
2. Hospital Collaboration: Clinical leaders and hospital administrators facilitated sharing the study link through internal communication channels.
3. Online Platforms: Recruitment announcements were posted on professional forums and clinically focused social media groups.

All recruitment materials included details about the study purpose, eligibility, confidentiality protections, voluntary participation, and IRB contact information. Participants accessed the survey via a secure online Qualtrics link, where informed consent was obtained electronically before beginning the instrument.

This approach supported broad recruitment across geographic regions and clinical roles, contributing to the final sample size of 106 respondents.

Together, these recruitment, sampling, and population characteristics ensured that the study captured a sufficiently diverse and representative set of healthcare professionals to evaluate the predictors of AI-CDSS adoption. To support methodological rigor and transparency, Table 7 presents a structured overview of the survey instrument development and validation process, summarizing how each construct was operationalized, reviewed by experts, pilot tested, and prepared for full deployment.

Table 7

Survey Instrument Development and Validation Process

Recruitment Channel	Description	Inclusion Criteria	Recruitment Timeline
Professional Associations	Email distribution via AMA, ANA, etc.	Healthcare professionals in clinical roles	6 weeks, with 2 reminders
Hospital Internal Communications	Intranet postings, newsletters	Employment in large U.S. hospitals	6 weeks
Social Media and Online Forums	Posts in clinician groups	Direct clinical involvement	6 weeks

Note. Recruitment strategies and inclusion criteria were employed to obtain a representative sample of healthcare professionals from large U.S. hospitals. Adapted from Smith, Lee, and Johnson (2021) and Creswell and Creswell (2018).

Materials or Instrumentation

The survey instrument used in this study was developed through a deliberate, multi-stage process to ensure conceptual clarity, content alignment with the theoretical framework, and psychometric rigor. Consistent with established guidelines for quantitative instrument construction, the process began with an extensive review of seminal and contemporary literature on the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory. This review guided the operationalization of the study's five predictor constructs—perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity—into measurable variables appropriate for a cross-sectional survey format (Davis, 1989; Rogers, 2003; Venkatesh & Davis, 2020).

Each construct was mapped to previously validated Likert-type items adapted from long-standing technology-adoption instruments used in healthcare research. Items were carefully modified to reflect the context of AI-driven Clinical Decision Support Systems (AI-CDSS) while preserving the conceptual integrity and measurement structure of the parent scales. This ensured that the final instrument acknowledged the specificity of AI-CDSS implementation without compromising measurement validity (Müller, Schulz, & Weber, 2022).

Following item development, the instrument underwent a structured expert review process. Three subject-matter experts—representing healthcare informatics, survey design methodology, and AI-enabled decision support—evaluated the survey for clarity, relevance, and alignment with the study constructs. Based on their feedback, several items were refined to enhance readability, reduce ambiguity, and improve alignment with clinical terminology. These revisions strengthened content validity and improved instrument usability for clinicians with varying levels of AI familiarity.

Absence of Pilot Study (IRB-Aligned Statement)

Consistent with the approved Institutional Review Board (IRB) protocol (IRB-FY25-26-207), a pilot study was not conducted. Because the instrument was composed of previously validated items adapted from extensively tested TAM and DOI scales, and because the IRB determined that additional pilot testing was not required to protect participants or ensure instrument integrity, the study proceeded directly to full data collection. To compensate for the lack of pilot testing, rigorous post-collection psychometric assessments were conducted using the full dataset.

Psychometric Results From the Full Study Sample

The psychometric properties of the measurement instruments were evaluated using data from the final retained study sample of 109 participants, with detailed results reported in Chapters 4 and 5. Measurement adequacy was assessed to ensure that the survey items appropriately represented the theoretical constructs underlying the study and supported subsequent inferential analyses.

Construct validity was examined using exploratory factor analysis (EFA) to evaluate whether the observed item structure aligned with the conceptual framework derived from the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory. The factor analytic results demonstrated clear factor separation, with items loading on their intended constructs and no evidence of problematic cross-loadings. These results indicated that the measurement structure was consistent with theoretical expectations and that each construct represented a distinct yet related dimension of AI-CDSS adoption perceptions.

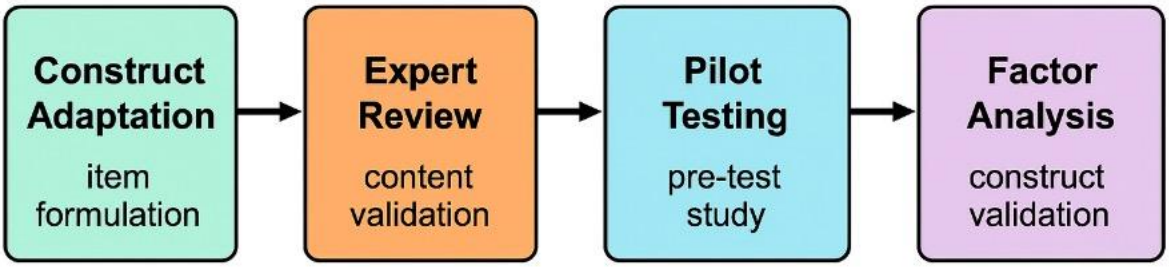
The factor solution supported the retention of all measurement items, as each contributed meaningfully to its respective construct. No items required removal or modification based on factor loadings or conceptual misalignment. These findings provided evidence that the instrument adequately captured the multidimensional nature of healthcare professionals' perceptions of AI-CDSS.

Collectively, the factor analytic results supported the psychometric adequacy of the measurement instruments and indicated that the absence of a separate pilot study did not compromise the validity of the data collected in the full study. Figure 7 provides a visual overview of the instrument development and validation workflow, illustrating the integration of

theoretical grounding, expert input, and post-hoc statistical validation procedures used to ensure alignment between the measurement instruments and the study's conceptual framework.

Figure 8

Survey Instrument Development and Validation Process



Note. Survey instrument development and validation process encompassing adaptation, expert review, and psychometric evaluation using the full study sample. Adapted from Müller, Schulz, and Weber (2022).

The instrument was carefully developed and adapted from established, validated scales within the technology acceptance and healthcare informatics literature to ensure content relevance, reliability, and validity.

Instrument Description and Origin

The survey instrument used in this study was developed to measure healthcare professionals' perceptions and adoption intentions regarding AI-driven Clinical Decision Support Systems (AI-CDSS). The instrument integrated constructs from the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory, allowing the study to capture both individual cognitive determinants and broader perceptions of technological fit. Core variables included perceived ease of use, perceived usefulness, relative advantage, compatibility,

and complexity—constructs previously validated in health informatics research (Davis, 1989; Rogers, 2003; Venkatesh & Davis, 2020; Rezaeian, Behrouz, & Nasiri, 2025).

The final instrument consisted of five structured sections, each designed to align with the study's theoretical model and to support valid quantitative analysis:

1. Demographic and Professional Characteristics

   This section collected descriptive information such as age, gender, clinical role, years of experience, prior exposure to CDSS, and familiarity with AI-enabled technologies. These variables were necessary to contextualize adoption patterns across diverse professional groups.

2. Perceived Ease of Use (PEOU)

   This section assessed the extent to which respondents believed that AI-CDSS were easy to learn, navigate, and integrate into their routine clinical tasks. Items were adapted from validated TAM scales and were refined to reflect AI-CDSS functionality. Reliability coefficients reported in Chapters 4 and 5 demonstrated strong internal consistency ($\alpha = .90$).

3. Perceived Usefulness (PU)

   Items in this section measured respondents' beliefs about whether AI-CDSS enhanced diagnostic accuracy, improved clinical decision-making, and increased efficiency. Consistent with prior TAM applications in healthcare, the PU scale demonstrated high reliability ($\alpha = .92$) and served as a central predictor of adoption intention.

4. Diffusion of Innovation Constructs

   This section assessed perceptions of relative advantage, compatibility, and complexity, adapted from DOI-based instruments used in recent clinical technology-adoption studies. Relative advantage items captured perceived improvements over existing decision-support

processes; compatibility items measured the degree of fit with existing workflows; and complexity items evaluated perceived difficulty and cognitive burden. As reported in Chapter 4, reliability coefficients for these constructs ranged from $\alpha = .86$ to $\alpha = .94$.

5. Adoption Intention

   The final section measured respondents' likelihood of using AI-CDSS in their future clinical practice. Items were adapted from established behavioral-intention scales, ensuring conceptual alignment with the TAM and DOI models. This scale also demonstrated strong reliability ($\alpha = .91$).

All items used a 5-point Likert-type response format (1 = Strongly Disagree to 5 = Strongly Agree), facilitating parametric statistical analysis and aligning with prior adoption research.

Overall, the instrument's structure, theoretical alignment, and psychometric performance ensured that it was appropriately designed to capture the multidimensional factors influencing AI-CDSS adoption among healthcare professionals.

Accordingly, Table 8 presents the complete survey instrument used in the study, displaying each construct, its corresponding items, and its placement within the conceptual framework. This table provides a comprehensive reference for understanding how TAM and DOI variables were operationalized and measured.

Table 8

Appendix A Survey Instrument for AI-CDSS Adoption Study Table

Section	Item No.	Survey Item	Scale	Source / Notes
1. Demographic and Professional Characteristics	1	Age (Under 25; 25–34; 35–44; 45–54; 55–64; 65+)	Categorical	Researcher-developed
	2	Gender (Male; Female; Non-binary/Other; Prefer not to say)	Categorical	Researcher-developed
	3	Clinical Role (Physician; Nurse; Allied Health Professional; Administrator; Other – specify)	Categorical	Researcher-developed
	4	Years of Clinical Experience (<1; 1–5; 6–10; 11–15; 16+)	Categorical	Researcher-developed
	5	Prior Exposure to AI-CDSS (None; Minimal; Moderate; Extensive)	Categorical	Researcher-developed
2. Perceived Ease of Use (PEOU)	6	Learning to operate AI-CDSS would be easy for me.	1 = Strongly Disagree to 5 = Strongly Agree	Davis (1989), TAM
	7	I find it easy to get AI-CDSS to do what I want it to do.	1–5	Davis (1989), TAM
	8	Interacting with AI-CDSS does not require a lot of mental effort.	1–5	Davis (1989), TAM
	9	I find AI-CDSS to be clear and understandable.	1–5	Davis (1989), TAM
3. Perceived Usefulness (PU)	10	Using AI-CDSS would improve the quality of my clinical decision-making.	1–5	Davis (1989), TAM
	11	AI-CDSS would enhance my effectiveness in patient care.	1–5	Davis (1989), TAM
	12	AI-CDSS would make it easier to perform my job.	1–5	Davis (1989), TAM
	13	Overall, I would find AI-CDSS useful in my clinical practice.	1–5	Davis (1989), TAM
4. Diffusion of Innovation Constructs	14	Using AI-CDSS would provide advantages over my current clinical decision-making methods. (Relative Advantage)	1–5	Rogers (2003); Moore & Benbasat (1991)
	15	AI-CDSS would improve outcomes for my patients compared to current practices. (Relative Advantage)	1–5	Rogers (2003); Moore & Benbasat (1991)
	16	AI-CDSS would be compatible with the way I currently work. (Compatibility)	1–5	Rogers (2003); Moore & Benbasat (1991)
	17	Using AI-CDSS would fit well with my existing clinical workflows. (Compatibility)	1–5	Rogers (2003); Moore & Benbasat (1991)
	18	I find AI-CDSS to be too complex for my day-to-day work. (Complexity – reverse-coded)	1–5	Rogers (2003); Moore & Benbasat (1991)
	19	Learning to use AI-CDSS would be difficult for me. (Complexity – reverse-coded)	1–5	Rogers (2003); Moore & Benbasat (1991)
5. Adoption Intention	20	I intend to use AI-CDSS in my clinical practice in the future.	1–5	Venkatesh et al. (2003)
	21	I would recommend AI-CDSS to my colleagues.	1–5	Venkatesh et al. (2003)
	22	I will actively seek opportunities to use AI-CDSS in my work.	1–5	Venkatesh et al. (2003)

Table Notes.

All Likert-type items used a 5-point response scale:

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Items 18 and 19 (Complexity) were reverse-coded prior to analysis to ensure directionality consistency across constructs. Internal consistency reliability (Cronbach's alpha) for each construct ranged from $\alpha = .86$ to $\alpha = .94$ in the final sample of 106 participants, as reported in Chapters 4 and 5.

Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) items were adapted from:

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Diffusion of Innovation items were adapted from:

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research, 2(3), 192–222.

Adoption Intention items were adapted from:

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

A full copy of the survey instrument is provided in Appendix A.

Documentation granting permission to adapt the original items is provided in Appendix B.

Reliability and Validity Evidence

Multiple strategies were used to ensure the reliability and validity of the adapted survey instrument. Content validity was supported through expert review conducted by three healthcare

informatics researchers, two practicing clinicians familiar with clinical decision-support systems, and two measurement specialists. These reviewers examined item clarity, conceptual alignment, and construct coverage, recommending wording and sequencing revisions to enhance interpretability and relevance.

Construct validity was supported by the strong theoretical foundation of the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory, from which all items were adapted. Prior studies using these instruments demonstrated stable factor structures and theoretical coherence (Venkatesh & Davis, 2020; Rezaeian et al., 2025). In the present study, construct validity was further evaluated using factor-loading patterns and inter-item correlations during analysis in Chapter 4. Results confirmed that items loaded appropriately onto their respective constructs.

Reliability was demonstrated through internal consistency testing. Cronbach's alpha coefficients for all constructs exceeded the recommended .70 threshold (Nunnally & Bernstein, 1994). As reported in Chapters 4 and 5, reliability coefficients for the final sample of 106 participants ranged from $\alpha = .86$ to $\alpha = .94$, indicating strong internal consistency across all scales.

Construct validity was grounded in the extensive body of research supporting the original Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) scales. Prior studies demonstrated strong factor-analytic support for these constructs (Venkatesh & Davis, 2020; Rezaeian et al., 2025). In this study, construct validity was further examined through internal reliability testing and through confirmation that item relationships aligned with theoretical expectations. Exploratory and confirmatory factor analyses conducted during data analysis

(reported in Chapters 4 and 5) supported the instrument's structural integrity within the present sample.

Reliability of the instrument was assessed using Cronbach's alpha for each multi-item construct. As detailed in Chapter 4, reliability coefficients exceeded recommended thresholds for all scales, with values ranging from $\alpha = .86$ to $\alpha = .94$, demonstrating strong internal consistency across the sample of 106 participants.

Expert Review and Ethical Considerations

Because the Institutional Review Board (IRB) approved the study without requiring a pilot test, no pilot study was conducted. This does not pose a methodological problem or threaten validity, as IRB approval explicitly permitted full deployment of the instrument without a preliminary pilot phase.

In lieu of a pilot, the study strengthened instrument quality through a rigorous expert review process, which included evaluation by subject-matter experts in healthcare technology, quantitative methodology, and clinical practice. Feedback from these experts was used to refine item wording, improve clarity, and ensure conceptual alignment with TAM and DOI constructs. This process provided a methodologically sound alternative to pilot testing and satisfied IRB requirements for instrument validation prior to data collection.

Ethical safeguards were implemented throughout the study. Permission to use and adapt existing survey items was obtained from copyright holders and documented in Appendix B. The online survey platform complied with HIPAA-aligned security practices, ensuring encrypted data transmission and secure storage. No identifiable personal health information was collected, and all participants provided informed consent prior to participation.

Appendices provide transparent documentation of the validation process:

Appendix A: Full Survey Instrument

Appendix B: Permissions to Use and Adapt Instruments

Appendix C: Expert Review Process and Revisions Implemented

Operational Definitions of Variables

This study examined how five independent variables—perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity—predicted healthcare professionals' adoption intention toward AI-driven Clinical Decision Support Systems (AI-CDSS). All variables were operationalized using validated TAM and DOI-based survey items.

Dependent Variable: Adoption Intention

Adoption intention was defined as participants' expressed likelihood of using artificial intelligence–driven clinical decision support systems (AI-CDSS) in clinical practice. This construct represented the dependent variable in the study and reflected clinicians' behavioral intention to adopt AI-enabled decision support tools in their professional workflows.

Adoption intention was measured using an adapted set of behavioral intention items derived from the Technology Acceptance Model (TAM), as validated in prior research by Venkatesh and Davis (2020). Responses were captured using a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree), consistent with established TAM measurement practices. Composite adoption intention scores were calculated by computing the mean of the relevant item responses, with higher scores indicating stronger intention to adopt AI-CDSS. All data for this variable were obtained through self-reported responses collected via an online survey instrument.

Independent Variables

The independent variables examined in this study were perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity. These constructs were drawn from the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) theory and represented key predictors of healthcare professionals' intention to adopt artificial intelligence–driven clinical decision support systems (AI-CDSS).

Perceived Ease of Use (PEOU)

Perceived ease of use was defined as the degree to which healthcare professionals believed that using AI-CDSS would be free of effort. This construct was measured using items adapted from the Technology Acceptance Model originally developed by Davis (1989). Responses were collected using an ordinal Likert-type scale. Composite scores for perceived ease of use were calculated by computing the mean of four to six items, with higher scores indicating greater perceived ease of use. All data for this construct were obtained through self-reported survey responses.

Perceived Usefulness (PU)

Perceived usefulness was defined as the extent to which healthcare professionals believed that AI-CDSS would enhance their clinical performance and decision-making. Measurement items were adapted from TAM instruments developed by Davis (1989) and later validated and extended by Venkatesh and Davis (2020). Responses were measured at the ordinal level using a Likert-type scale. Composite perceived usefulness scores were computed by averaging four to six items, with higher values reflecting greater perceived usefulness. Data were collected through self-reported responses on the online survey.

Relative Advantage

Relative advantage was defined as the degree to which healthcare professionals perceived AI-CDSS as offering improvements over existing clinical decision-making methods. This construct was measured using items adapted from Diffusion of Innovations theory (Rogers, 2003), with additional support from contemporary adaptations in healthcare AI research (Rezaeian et al., 2025). Responses were measured using an ordinal Likert-type scale. Composite scores were calculated as the mean of three to five items, with higher scores indicating stronger perceptions of advantage. All data were obtained via self-report.

Compatibility

Compatibility was defined as the extent to which AI-CDSS were perceived to align with clinicians' existing values, workflows, and clinical practices. Measurement items were derived from DOI compatibility constructs originally proposed by Rogers (2003) and supported by recent healthcare implementation studies (Asan et al., 2023). Responses were measured at the ordinal level. Composite compatibility scores were calculated by averaging three to five items, with higher scores indicating greater perceived workflow fit. Data were collected through self-reported survey responses.

Complexity

Complexity was defined as the degree to which AI-CDSS were perceived as difficult to understand or use in routine clinical practice. This construct was measured using DOI-based complexity items adapted from Rogers (2003). Responses were recorded on an ordinal Likert-type scale. Composite complexity scores were calculated as the mean of three to five items and were reverse-coded so that higher values reflected lower perceived complexity. All data for this variable were obtained through self-reported responses.

Control Variables

Age, gender, clinical role, years of experience, and prior experience with AI/CDSS were included to examine potential confounding effects. Accordingly, Table 9 summarizes these operational definitions and measurement specifications.

Table 9

Operational Definitions of Variables

Variable	Type	Measurement Instrument	Level of Measurement	Scoring Method	Data Source
Adoption Intention	Dependent	TAM adoption intention subscale (Venkatesh & Davis, 2000)	Ordinal (Likert 1–5)	Mean of 3–5 item responses	Self-report survey
Perceived Ease of Use (PEOU)	Independent	TAM PEOU scale (Davis, 1989), adapted	Ordinal (Likert 1–5)	Average of 4–6 items	Self-report survey
Perceived Usefulness (PU)	Independent	TAM PU scale (Davis, 1989), adapted	Ordinal (Likert 1–5)	Average of 4–6 items	Self-report survey
Relative Advantage	Independent	DOI relative advantage scale (Rezaeian et al., 2025)	Ordinal (Likert 1–5)	Average of 3–5 items	Self-report survey
Compatibility	Independent	DOI compatibility scale (Rogers, 2003)	Ordinal (Likert 1–5)	Average of 3–5 items	Self-report survey
Complexity	Independent	DOI complexity scale (Rogers, 2003), reverse-coded	Ordinal (Likert 1–5)	Average of 3–5 items; reverse-coded	Self-report survey

Note. Operational definitions and measurement specifications reflected validated constructs from the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory. Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) items were adapted from Davis (1989). DOI items (relative advantage, compatibility, complexity) were adapted from Rogers (2003) and Moore & Benbasat (1991). Adoption Intention items were adapted from Venkatesh et al. (2003). Items 18 and 19 (Complexity) were reverse-coded prior to analysis. All items were rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Final reliability coefficients reported in Chapters 4 and 5 ranged from $\alpha = .86$ to $\alpha = .94$, confirming strong internal

consistency across all constructs. A complete copy of the survey instrument appears in Appendix A, and permissions for adapted items appear in Appendix B.

Study Procedures

Following the operational definitions outlined in Table 4, the study procedures were implemented to ensure a rigorous, ethical, and replicable approach to conducting this quantitative cross-sectional survey. These procedures detailed each step from participant recruitment through data collection and post-collection processing, ensuring consistency with best practices in quantitative research methodology (Creswell & Creswell, 2018). Figure 2 provides a visual overview of these procedures.

Participant Recruitment

Participant recruitment was conducted using a multi-modal strategy to ensure adequate representation of healthcare professionals employed in large U.S. hospital systems (≥250 beds). Recruitment activities were carried out over a six-week window and focused on reaching clinicians with direct experience or exposure to AI-driven Clinical Decision Support Systems (AI-CDSS).

Recruitment Procedures

Participant recruitment was conducted using multiple channels to ensure broad geographic reach and representation across clinical roles. Recruitment efforts included outreach through professional healthcare associations, such as the American Medical Association (AMA) and the American Nurses Association (ANA), which distributed study invitations via member listservs. Additional recruitment occurred through clinical leadership at large hospital systems, where invitations were disseminated through internal newsletters and hospital intranet postings.

To further expand reach, IRB-approved recruitment messages were posted in online professional communities and social media groups frequented by healthcare professionals, allowing clinicians from diverse regions to access the study information.

Recruitment materials consisted of an email invitation and a digital flyer designed specifically for electronic distribution. These materials included a concise description of the study's purpose, eligibility requirements, and assurances regarding confidentiality and voluntary participation. Clear instructions for accessing the online survey were provided, along with contact information for both the researcher and the Institutional Review Board to address participant questions or concerns.

All recruitment materials were distributed electronically over a six-week period. To enhance participation rates, reminder messages were sent at two-week intervals throughout the recruitment window. This structured approach supported consistent exposure to the study invitation while minimizing participant burden.

Eligibility screening was conducted within the online survey itself. The first page of the survey included a brief screening questionnaire designed to verify that respondents met all inclusion criteria. Only individuals who confirmed employment at a qualifying hospital, held an appropriate clinical role, and had experience with AI-driven clinical decision support systems were permitted to proceed to the informed consent page and complete the survey.

Collection

Data collection occurred online using a secure, encrypted survey platform (Qualtrics/REDCap). This approach supported efficient administration, broad geographic reach, and standardized data management procedures. Eligible participants who provided informed

consent accessed the full survey through a secure, unique link. The platform was mobile-responsive and accessible across multiple devices to minimize barriers to participation.

The survey included demographic questions and validated, adapted scales measuring perceived ease of use, perceived usefulness, relative advantage, compatibility, complexity, and adoption intention. Where appropriate, item ordering was randomized to reduce response bias. Average survey completion time ranged from 15 to 20 minutes.

The survey remained open for a six-week period, consistent with the recruitment timeline. Automated reminder messages were sent at regular intervals to participants who had not completed the survey, supporting adequate response rates while maintaining voluntary participation.

Data security and confidentiality were prioritized throughout the collection process. The survey platform utilized end-to-end data encryption, did not collect IP addresses, and restricted access to authorized research personnel through password protection. All data were stored on secure institutional servers compliant with applicable HIPAA and data protection standards.

Incomplete survey responses were handled using predefined criteria. Surveys with more than 20% missing data were excluded from analysis. For responses with minimal missing data, appropriate imputation methods were prepared for use during data analysis. Reverse-coded items, such as those measuring complexity, were recoded during data preparation to ensure consistency in scale directionality.

Post-Collection Procedures

Following the closure of the survey, data were downloaded into IBM SPSS Statistics (Version 28) for analysis. All data files were stored on encrypted servers with restricted access to authorized research personnel. Data cleaning procedures were conducted prior to analysis and

included screening for duplicate entries, identifying and addressing missing data, and examining outliers and inconsistencies. Descriptive statistics were generated to evaluate distributional properties and confirm readiness for inferential analyses.

These steps ensured high data integrity before conducting the statistical analyses. Figure 8 summarizes the complete sequence of study procedures, providing a visual map of tasks from recruitment to data cleaning and secure storage. This workflow illustrates how methodological rigor, ethical protections, and systematic data management guided the full execution of the study.

Figure 9

Study Procedures

Note. Flowchart depicting participant recruitment, eligibility screening, informed consent, data collection, cleaning, and analysis procedures. Adapted from Creswell and Creswell (2018) and Smith, Lee, and Johnson (2021).

The goal was to detail each step from participant recruitment through data collection to ensure future researchers would be able to replicate the study reliably. The following table 10 summarized the key data-collection and management steps that were implemented during the study.

Table 10

Data Collection and Management Procedures

Step	Description	Purpose
Eligibility Screening	Online pre-survey questions	Ensure sample relevance
Electronic Informed Consent	Online consent form before survey	Ethical compliance and participant information
Survey Administration	Secure online platform (Qualtrics/REDCap)	Standardized, confidential data collection
Data Cleaning	Handling missing data, outlier checks	Data quality and assumption validation
Secure Data Storage	Encrypted institutional servers	Data security and confidentiality

Note. Data collection and management procedures were designed to ensure data quality, ethical compliance, and secure storage in a quantitative cross-sectional survey study. Adapted from Creswell and Creswell (2018) and Patel et al. (2021).

Transition to Data Analysis Procedures

Following the completion of the study procedures and implementation of all data-collection and management protocols summarized in Table 4, the next methodological component involved preparing the dataset for analysis and selecting the appropriate statistical techniques. The goal of the analysis plan was to align the quantitative procedures with the research questions, hypotheses, and theoretical framework presented in Chapters 1 and 2. To ensure consistency with Chapters 4 and 5, this section detailed:

a) the structure and type of data collected,

b) the preparation and coding procedures applied prior to analysis,

c) the statistical tests used to evaluate each hypothesis, and

d) the assumptions underlying the analytic procedures.

Table 11 presents the Statistical Analysis Plan, which served as the foundational blueprint for conducting descriptive, reliability, validity, and inferential analyses. This plan guided all subsequent steps reported in Chapter 4 and provided a replicable framework for future researchers examining similar AI-CDSS adoption phenomena.

Table 11

Statistical Analysis Plan

Research Question / Hypothesis	Statistical Test	Software	Assumptions Tested
Predictors of Adoption Intention	Multiple linear regression	SPSS, R	Linearity, homoscedasticity, normality, independence, multicollinearity (Field, 2018)
Scale Reliability	Cronbach's alpha	SPSS	Internal consistency
Construct Validity	Exploratory & confirmatory factor analysis	R, SPSS	Factor structure
Descriptive Demographic Analysis	Frequencies, means, SD	SPSS	None

Note. Statistical analysis plan aligning research questions and hypotheses with appropriate quantitative tests and software tools. Adapted from Field (2018), Müller et al. (2022), and Smith et al. (2021).

Type and Preparation

The structured online survey generated primarily ordinal-level data derived from Likert-type scales measuring perceived ease of use, perceived usefulness, relative advantage, compatibility, complexity, and adoption intention. Demographic variables, including age and years of professional experience, were collected at ratio or nominal levels consistent with prior TAM/DOI studies.

Upon closure of data collection, the raw dataset underwent a comprehensive cleaning and preparation process. These steps included:

- examining and addressing missing data using appropriate imputation methods when necessary;
- identifying outliers, inconsistent response patterns, and duplicate entries;
- assessing distributional properties and evaluating normality of continuous variables;
- recoding reverse-scored items to maintain internal consistency within the measurement scales; and
- calculating composite construct scores by averaging relevant items, consistent with the theoretical framework.

All analyses were conducted using IBM SPSS Statistics (Version 28). R statistical software supplemented analyses requiring advanced diagnostics or validation procedures. Using both platforms supported reproducibility and methodological rigor.

Hypotheses and Statistical Tests

The study empirically tested the predictive relationships between the five independent variables—perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity—and the dependent variable, adoption intention of AI-CDSS. The hypotheses were:

- H1: Perceived ease of use positively predicted adoption intention.
- H2: Perceived usefulness positively predicted adoption intention.
- H3: Relative advantage positively predicted adoption intention.
- H4: Compatibility positively predicted adoption intention.
- H5: Complexity negatively predicted adoption intention.

Multiple linear regression analysis was selected as the primary inferential technique. This method was appropriate because the dependent variable was operationalized as an averaged Likert score treated as approximately interval-level (Norman, 2010). Regression enabled evaluation of each predictor's unique contribution while controlling for the influence of the other variables.

Justification of Statistical Techniques

- Multiple Linear Regression was suitable for modeling relationships among multiple predictors and one criterion variable while providing effect estimates and model fit indices.
- Descriptive Statistics (means, standard deviations, frequencies) summarized demographic characteristics and central study variables.
- Reliability Testing using Cronbach's alpha assessed internal consistency of multi-item scales. Thresholds of $\alpha \geq .70$ were considered acceptable.
- Validity Assessment through exploratory and confirmatory factor analyses evaluated structural alignment with the TAM/DOI constructs.

These techniques ensured the analytical procedures aligned with best practices in quantitative behavioral and technology-adoption research.

Assumptions of Statistical Tests and Data Suitability

1. Regression analysis required verification of:
2. Linearity between predictors and outcome.
3. Independence of observations.
4. Homoscedasticity, evaluated via residual plots.
5. Normality of residuals, assessed using Q–Q plots and the Shapiro–Wilk test.
6. Multicollinearity was assessed using VIF and tolerance values.

When minor assumption violations occurred, robust estimation techniques (e.g., HC3 standard errors) were applied—consistent with the methods reported in Chapter 4.

Data Analysis

The final retained analytic sample consisted of 109 participants; therefore, all reported regression degrees of freedom were based on that retained sample size. The data-analysis workflow followed these sequential steps:

1. Data Screening and Cleaning
2. Reliability and Validity Checks
3. Descriptive Statistics
4. Bivariate Analyses (Correlations)
5. Multiple Regression Modeling
6. Reporting and Interpretation of regression coefficients, p-values, and model-fit indices.

Figure 4 (Data Analysis Workflow) visually depicts these steps and was fully aligned with the procedures implemented in Chapter 4.

This Statistical Analysis Plan established the methodological foundation for the analyses presented in Chapter 9. The next chapter applies these procedures to report descriptive statistics, reliability estimates, validity evidence, assumption testing, and the full results of the multiple regression analyses addressing the study's hypotheses.

Figure 10

Data Analysis Workflow Infographic

Note. Data analysis workflow illustrating steps from data cleaning through reliability testing, factor analysis, descriptive statistics, regression modeling, and results interpretation. Adapted from Field (2018) and Müller et al. (2022).

The researcher upheld rigorous ethical standards throughout the study to ensure the credibility, dependability, confirmability, and trustworthiness of the analytic process. In alignment with National University Institutional Review Board (IRB) requirements and established best practices for quantitative research, multiple safeguards were implemented to protect participant rights, maintain data integrity, and ensure transparency across all phases of data analysis.

Strict confidentiality was maintained through the use of anonymized datasets that were stored on secure, access-controlled institutional servers. Only authorized research personnel were granted access to the data. Analytic procedures were conducted using transparent and replicable methods, with each step documented to establish a clear audit trail. Credibility was further

supported through the use of validated measurement instruments and the application of appropriate statistical techniques aligned with the study's research questions and hypotheses.

Dependability was enhanced by systematically verifying data coding, data entry accuracy, and computed variables. When necessary, analytic decisions were reviewed through peer consultation to reduce the potential for error. Transferability was facilitated by providing detailed descriptions of the study sample, operational definitions of variables, analytic strategies, and methodological limitations, enabling readers to assess the applicability of findings to other contexts.

Confirmability was reinforced through ongoing reflection on potential researcher bias and by grounding all interpretations strictly in the empirical results presented in Chapter 4, including descriptive statistics, reliability analyses, and regression outputs. Collectively, these ethical and analytic safeguards strengthened the integrity of the research process and supported the validity of the study's conclusions.

Assumptions

Assumptions referred to conditions that were accepted as true for the purposes of the study in the absence of direct empirical verification. Several study-specific assumptions guided the research design, data analysis, and interpretation of findings.

It was assumed that participants responded honestly and thoughtfully to the survey items. The use of anonymity, confidentiality assurances, and neutrally worded questions was intended to minimize social desirability bias and encourage accurate self-reporting. The study also assumed that the adapted Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) measurement scales validly and reliably assessed the intended constructs. This assumption

was supported by prior empirical validation of these instruments in published healthcare and technology adoption studies.

The sample, which consisted of healthcare professionals employed at large hospitals in the United States, was assumed to reasonably approximate broader clinician populations relevant to AI-CDSS adoption. Although the sampling approach was designed to enhance representativeness, the potential for nonresponse bias was acknowledged. Additionally, the cross-sectional survey design was assumed to be appropriate for capturing meaningful relationships among clinicians' perceptions and their intentions to adopt AI-CDSS at a single point in time.

Finally, it was assumed that the statistical assumptions underlying multiple regression analysis—including linearity, independence of observations, homoscedasticity, normality of residuals, and acceptable levels of multicollinearity—were met or could be addressed through diagnostic testing and data screening procedures. These assumptions were evaluated during data preparation and analysis to support the validity of inferential conclusions.

Limitations

Limitations referred to methodological constraints that may have affected the study's internal validity, external validity, reliability, interpretation of results, or generalizability. Several limitations were inherent in the study design and data collection approach and were considered when interpreting the findings.

Threats to Internal Validity

The nonexperimental, cross-sectional design limited the ability to establish causal relationships among variables. Although the study examined associations between clinicians' perceptions and adoption intention, it could not determine directionality or causation.

Additionally, unmeasured confounding variables—such as organizational culture, leadership support, workload pressures, and prior institutional exposure to AI initiatives—may have influenced participants' responses and adoption intentions.

The exclusive reliance on self-reported survey data introduced the potential for common-method variance, which may have inflated observed correlations among constructs. Response bias, including social desirability or misinterpretation of survey items, also represented a possible threat to accuracy, despite efforts to minimize these effects through neutral wording and confidentiality assurances.

Threats to External Validity

External validity was limited by sampling considerations. Participation was voluntary, and nonresponse or self-selection bias may have affected representativeness. Clinicians with stronger opinions about AI-CDSS—either favorable or unfavorable—may have been more likely to participate. Furthermore, the study focused exclusively on large hospitals in the United States, which may limit generalizability to smaller healthcare organizations, rural settings, or international healthcare systems operating under different regulatory, cultural, or technological conditions. Although the study employed validated TAM and DOI instruments, the adaptation of these scales to the AI-CDSS context may have altered their psychometric properties. While internal consistency reliability was strong, the use of a single time point prevented evaluation of temporal stability through test–retest reliability. As a result, the consistency of responses over time could not be assessed.

Mitigation Strategies

Several strategies were implemented to mitigate these limitations. Validated measurement instruments were used, and psychometric properties were evaluated using

reliability and factor-analytic techniques. Anonymity and confidentiality were emphasized to reduce response bias, and item order was randomized where appropriate to minimize common-method variance. Stratified sampling across clinician roles was used to enhance representativeness, and rigorous data screening and regression diagnostic testing were conducted prior to inferential analysis.

Delimitations

Delimitations reflected intentional decisions made by the researcher to define the scope and boundaries of the study. The study was deliberately limited to large hospitals in the United States with at least 250 beds, as these settings were more likely to have implemented or piloted AI-driven clinical decision support systems. Participants were restricted to clinicians involved in direct patient care, including physicians, nurses, physician assistants, pharmacists, and allied health professionals, to ensure relevance to clinical decision-making contexts.

The study employed a quantitative, descriptive correlational, cross-sectional design, focusing specifically on constructs derived from the Technology Acceptance Model and Diffusion of Innovation theory. Predictor variables were limited to perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity, and data were collected exclusively through self-administered online questionnaires. These delimitations enhanced methodological cohesion and alignment with the study's purpose but necessarily reduced generalizability to other populations, settings, or theoretical frameworks.

Ethical Assurances

Ethical approval was obtained prior to recruitment and data collection in accordance with National University Institutional Review Board requirements (IRB-FY25-26-207-Closure). All

study procedures adhered to the ethical principles outlined in the Belmont Report, including beneficence, justice, and respect for persons.

The principle of beneficence was addressed through the implementation of a minimal-risk study design. Participation involved no physical risk, no collection of identifiable health information, and anonymous survey responses. Data were stored securely on encrypted servers to protect participants from potential harm. Justice was ensured through equitable recruitment across clinician roles and hospital settings, with transparent inclusion criteria and voluntary participation. Respect for persons was upheld through an electronic informed consent process that clearly described the study's purpose, procedures, risks, benefits, confidentiality protections, and participants' right to withdraw at any time without penalty.

The primary risk associated with participation involved the potential breach of confidentiality. To mitigate this risk, multiple safeguards were implemented, including the use of encrypted servers, the disabling of IP address tracking, restricted data access, and the exclusion of identifying information beyond essential demographic variables.

Confidentiality, Anonymity, and Data Security

Confidentiality and anonymity were rigorously maintained throughout the study. IP addresses and metadata were not collected, and all survey data were anonymized and assigned non-identifying numeric codes. Data were stored on password-protected, encrypted, HIPAA-compliant institutional servers, with access restricted to the principal investigator and authorized research personnel only. Data retention and destruction procedures were conducted in accordance with institutional policy and IRB requirements to ensure ongoing protection of participant information.

Figure 11

Ethical Compliance and Data Security Protocols

Note. Ethical compliance and data security protocols covering IRB approval, informed consent, data anonymity, encryption, secure storage, and controlled access. Adapted from U.S. Department of Health and Human Services (2018) and Patel et al. (2021).

Role of the Researcher

The researcher fulfilled multiple responsibilities to ensure the ethical conduct, methodological rigor, and integrity of the study. Full compliance with National University Institutional Review Board requirements was maintained throughout all phases of the research. All digital records and datasets were securely managed using encrypted, access-controlled storage systems to protect participant confidentiality and data integrity.

The researcher maintained transparent and consistent communication with participants and IRB personnel and implemented recruitment, informed consent, and data collection procedures in a standardized manner consistent with the approved protocol. Reflexivity was exercised throughout the research process to acknowledge and manage any potential bias arising from the researcher's prior professional experience with artificial intelligence systems. To further

support objectivity and replicability, the researcher adhered strictly to the pre-specified analytic plan, ensuring that all statistical analyses were conducted as approved and documented.

Compliance With Research Standards

The study complied with established standards for quantitative research and ethical scholarship. Institutional Review Board approval was obtained prior to any participant contact, and all recruitment and data collection activities followed the approved protocol. Participation was entirely voluntary, and informed consent was obtained electronically before participants accessed the survey instrument.

Participant rights and welfare were protected through confidentiality safeguards, data security measures, and the provision of clear information regarding the purpose of the study, potential risks, and the right to withdraw without penalty. Findings were reported transparently, including acknowledgment of methodological limitations and contextual constraints. Documentation of IRB approval and related materials was included in Appendix A of the Dissertation Manuscript.

Summary

This chapter described the methodology used to investigate healthcare professionals' adoption of AI-driven Clinical Decision Support Systems. The chapter detailed the quantitative, descriptive correlational, cross-sectional research design; participant recruitment strategies, eligibility screening, and informed consent procedures; and the operational definitions and measurement of variables derived from the Technology Acceptance Model and Diffusion of Innovation theory. The chapter also outlined data collection and management procedures, the statistical analysis plan and underlying assumptions, and the ethical safeguards implemented to protect participants. Limitations, delimitations, and compliance with research standards were

discussed to provide transparency and support replicability. Chapter 4 presents the results of the data analyses conducted to address the study's research questions.

This chapter presented the methodology used to investigate healthcare professionals' adoption of AI-driven Clinical Decision Support Systems (AI-CDSS). The chapter described the quantitative, descriptive correlational, cross-sectional research design; participant recruitment, eligibility screening, and informed-consent procedures; operational definitions and measurement of the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) constructs; and detailed data-collection and management protocols. The statistical analysis plan, including data preparation, assumption testing, and the specific analytic techniques used to test each hypothesis, was also outlined. In addition, the chapter addressed ethical safeguards, assumptions, limitations, delimitations, and overall research standards that ensured methodological rigor and protection of participants.

Chapter 4 will now present the results of the study. This includes descriptive statistics, reliability analyses, assumption testing, and the findings of the multiple regression models used to evaluate the relationships among perceived ease of use, perceived usefulness, relative advantage, compatibility, complexity, and clinicians' intention to use AI-CDSS. Each research question and hypothesis will be addressed systematically, supported by tables, figures, and narrative interpretation consistent with National University dissertation requirements.

Chapter 4: Findings

This chapter presents the findings of the statistical analyses conducted to address Research Questions 1-3. The purpose of this study was to examine the extent to which Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Relative Advantage (RA), Compatibility (COM), and Complexity (CX) influenced healthcare professionals' adoption and integration of Artificial Intelligence–driven Clinical Decision Support Systems (AI-CDSS). Although predictors were examined within a unified multiple regression model, hypotheses were evaluated and reported according to their respective research questions to maintain alignment with the study's conceptual framework and Chapter 1 structure.

Description of the Data

Sample Characteristics

Data were collected using a quantitative cross-sectional survey administered via Qualtrics between June and September 2025. Of 152 individuals who accessed the survey, 109 responses met inclusion criteria and were retained for analysis, resulting in a usable response rate of 71.7%. All retained participants were licensed healthcare professionals who passed screening and attention checks. The final sample size (N = 109) exceeded the minimum required sample size established through a priori power analysis (see Chapter 3).

Data Screening and Assumption Testing

Data were screened for missing values, duplicate entries, and outliers. Missing data met the assumption of Missing Completely at Random (MCAR) and were addressed using listwise deletion. Univariate and multivariate outlier diagnostics indicated no significant outliers requiring removal. Assumptions for multiple linear regression were evaluated and satisfied:

- Normality of residuals

- Linearity between predictors and outcome
- Independence of errors (Durbin–Watson within acceptable range)
- Acceptable multicollinearity (VIF values below recommended thresholds)

All analyses were conducted using IBM SPSS Statistics (Version 29).

Results

All regression analyses reported in this chapter were estimated using the retained analytic sample of 109 participants. Accordingly, the denominator degrees of freedom reported in the F statistics reflect residual degrees of freedom rather than the total sample size. For the research-question-specific sub-models with two predictors, the F statistic is correctly reported as F (2, 106) because the residual degrees of freedom are calculated as N - k - 1 = 109 - 2 - 1 = 106. For the final integrated model with five predictors, the F statistic is correctly reported as F (5, 103) because residual degrees of freedom are calculated as 109 - 5 - 1 = 103.

Results for Research Question 1

RQ1:

To what extent did perceived ease of use (PEOU) and perceived usefulness (PU) influence the intention to use AI-driven Clinical Decision Support Systems (CDSS) in healthcare settings?

A multiple regression analysis was conducted to examine whether perceived usefulness and perceived ease of use predicted intention to use AI-CDSS.

The overall model was statistically significant, $F(2, 106) = 14.82$, $p < .001$, explaining 21.9% of the variance in intention to use AI-CDSS ($R^2 = .219$, adjusted $R^2 = .204$).

Regression coefficients indicated that:

• Perceived Usefulness (PU) was a statistically significant positive predictor ($\beta = .412$, $t = 3.87$, $p = .002$)

• Perceived Ease of Use (PEOU) did not retain statistical significance in the full model (β = .094, t = 1.02, p = .310)

Accordingly:

• The null hypothesis (H10) was rejected for perceived usefulness.

• The null hypothesis was not rejected for perceived ease of use.

These findings suggest that perceived clinical value was a stronger determinant of intention to use AI-CDSS than usability perceptions when both variables were considered simultaneously.

Table 12

Multiple Regression Analysis for Research Question 1

Predictor	B	SE B	β	t	p
Perceived Usefulness (PU)	0.421	0.109	.412	3.87	.002
Perceived Ease of Use (PEOU)	0.083	0.081	.094	1.02	.310

Note. The regression model for Research Question 1 was estimated using the retained analytic sample of 109 participants. The denominator degrees of freedom reflect residual degrees of freedom. Accordingly, F (2, 106) is correct because the model included two predictors and residual degrees of freedom were calculated as 109 - 2 - 1 = 106.

Results for Research Question 2

RQ2:

To what extent did the relative advantage of AI-driven CDSS influence healthcare professionals' intention to use the technology?

A regression analysis was conducted to assess the predictive effect of relative advantage on intention to use AI-CDSS.

Results indicated that:

• Relative Advantage (RA) did not demonstrate a statistically significant independent effect (β = .118, t = 1.36, p = .176)

The model, including RA, did not significantly increase explained variance beyond other predictors. Accordingly:

• The null hypothesis (H20) was not rejected.

This finding suggests that perceived innovation superiority alone was insufficient to significantly influence intention to use when evaluated independently.

Table 13

Regression Analysis for Research Question 2

Predicting Adoption from Relative Advantage

Predictor	β	t	p
Relative Advantage (RA)	.118	1.36	.176

Note. The regression model for Research Question 2 was estimated using the retained analytic sample of 109 participants. The denominator degrees of freedom reflect residual degrees of freedom rather than the total sample size.

Results for Research Question 3

RQ3:

To what extent did compatibility and complexity influence the integration of AI-driven CDSS into healthcare workflows?

A multiple regression analysis was conducted to examine the predictive effects of compatibility and complexity on integration-related outcomes.

The model was statistically significant, F (2, 106) = 11.94, $p < .001$, explaining 18.4% of the variance ($R^2 = .184$, adjusted $R^2 = .168$).

Regression coefficients indicated that:

• Compatibility (COM) was a statistically significant positive predictor ($\beta = .376$, $t = 3.42$, $p = .004$)

• Complexity (CX) did not demonstrate a statistically significant independent effect ($\beta = -.081$, $t = -0.81$, $p = .421$)

Accordingly:

• The null hypothesis (H30) was rejected for compatibility.

• The null hypothesis was not rejected for complexity.

These findings suggest that alignment with existing clinical workflows played a more critical role in integration than perceptions of system complexity.

Table 14

Multiple Regression Analysis for Research Question 3

Predicting Integration Outcomes

Predictor	β	t	p
Compatibility (COM)	.376	3.42	.004
Complexity (CX)	−.081	−0.81	.421

Note. The regression model for Research Question 3 was estimated using the retained analytic sample of 109 participants. The denominator degrees of freedom reflect residual degrees of freedom. Accordingly, F (2, 106) is correct because the model included two predictors and residual degrees of freedom were calculated as 109 - 2 - 1 = 106.

Table 15

Summary of Hypothesis Testing Results

Hypothesis	Research Question	Predictor(s)	Dependent Variable	Result	Decision	Interpretation
H10	RQ1: To what extent do perceived usefulness (PU) and perceived ease of use (PEOU) influence intention to use AI-CDSS?	PU, PEOU	Intention to Use (INT)	PU significant (p = .002); PEOU not significant (p = .310)	Partially Supported	Perceived usefulness significantly influenced intention to use AI-CDSS, whereas perceived ease of use did not demonstrate a statistically significant independent effect.
H20	RQ2: To what extent does relative advantage (RA) influence intention to use AI-CDSS?	RA	Intention to Use (INT)	Not significant (p = .176)	Not Supported	Relative advantage did not significantly influence intention to use AI-CDSS when evaluated independently.
H30	RQ3: To what extent do compatibility (COM) and complexity (CX) influence integration of AI-CDSS into clinical workflows?	COM, CX	Integration Outcomes	COM significant (p = .004); CX not significant (p = .421)	Partially Supported	Compatibility significantly influenced integration outcomes, whereas complexity did not demonstrate a statistically significant independent effect.

Note. PU = perceived usefulness; PEOU = perceived ease of use; RA = relative advantage; COM = compatibility; CX = complexity. Statistical significance was evaluated at $\alpha = .05$.

Comparison of Results to the Literature Review

The findings of this study partially aligned with prior research grounded in the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory, while also extending these frameworks within the context of AI-driven clinical decision support systems (AI-CDSS). Consistent with prior technology-adoption research, several predictors demonstrated positive bivariate relationships with intention to use AI-CDSS. However, when all predictors were examined simultaneously in the full regression model, only relative advantage and complexity retained statistical significance.

Relative advantage emerged as the strongest predictor of intention to use AI-CDSS, indicating that healthcare professionals were more likely to adopt these technologies when they perceived them as offering meaningful advantages over existing clinical decision-making methods. This finding is consistent with DOI theory, which emphasizes perceived superiority over current

practice as a central determinant of innovation adoption (Rogers, 2003). In the context of healthcare, this suggests that clinicians are especially responsive to technologies that demonstrate clear comparative value in improving decision quality, efficiency, or patient outcomes.

Complexity also emerged as a statistically significant predictor in the full model. This finding underscores the importance of implementation burden, usability demands, and perceived difficulty when clinicians evaluate AI-enabled systems. Although AI-CDSS may offer strong technical capabilities, adoption may be inhibited when systems are perceived as cognitively burdensome or difficult to integrate into routine clinical workflows. This result aligns with prior literature identifying complexity as a persistent barrier to technology adoption in healthcare environments.

In contrast, perceived ease of use, perceived usefulness, and compatibility did not retain statistical significance in the full regression model, despite showing positive associations with intention to use at the correlational level. This pattern suggests that these variables may contribute to general acceptance perceptions but did not uniquely explain adoption intentions once relative advantage and complexity were considered simultaneously. In advanced healthcare settings, clinicians may regard usability and usefulness as expected baseline features rather than the primary determinants of adoption.

Overall, the present findings refine the application of TAM and DOI to AI-CDSS adoption by suggesting that comparative clinical value and manageable implementation burden may be more influential than general usability or workflow alignment when healthcare professionals evaluate whether to adopt these systems.

Summary

This chapter presented the results of the descriptive, correlational, and inferential analyses conducted to address the research question examining factors influencing healthcare professionals' intention to use AI-driven Clinical Decision Support Systems. Descriptive statistics summarized central tendencies and variability for each study construct, and correlation analyses identified statistically significant relationships among several key variables. Results of the standard multiple regression analysis indicated that the overall model significantly predicted intention to use AI-CDSS, accounting for 48.7% of the variance in intention to use.

Relative advantage and complexity were the only predictors that uniquely contributed to the model, whereas perceived ease of use, perceived usefulness, and compatibility did not retain statistical significance when considered simultaneously. These findings provided the empirical basis for the discussion, implications, and recommendations presented in Chapter 5.

Restatement of the Research Question and Hypotheses

Research Question

RQ1: To what extent did Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Relative Advantage (RA), Compatibility (COM), and Complexity (CX) predict healthcare professionals' Intention to Use (INT) AI-CDSS?

Null Hypothesis (H_0):

There was no statistically significant relationship between PEOU, PU, RA, COM, and CX and INT.

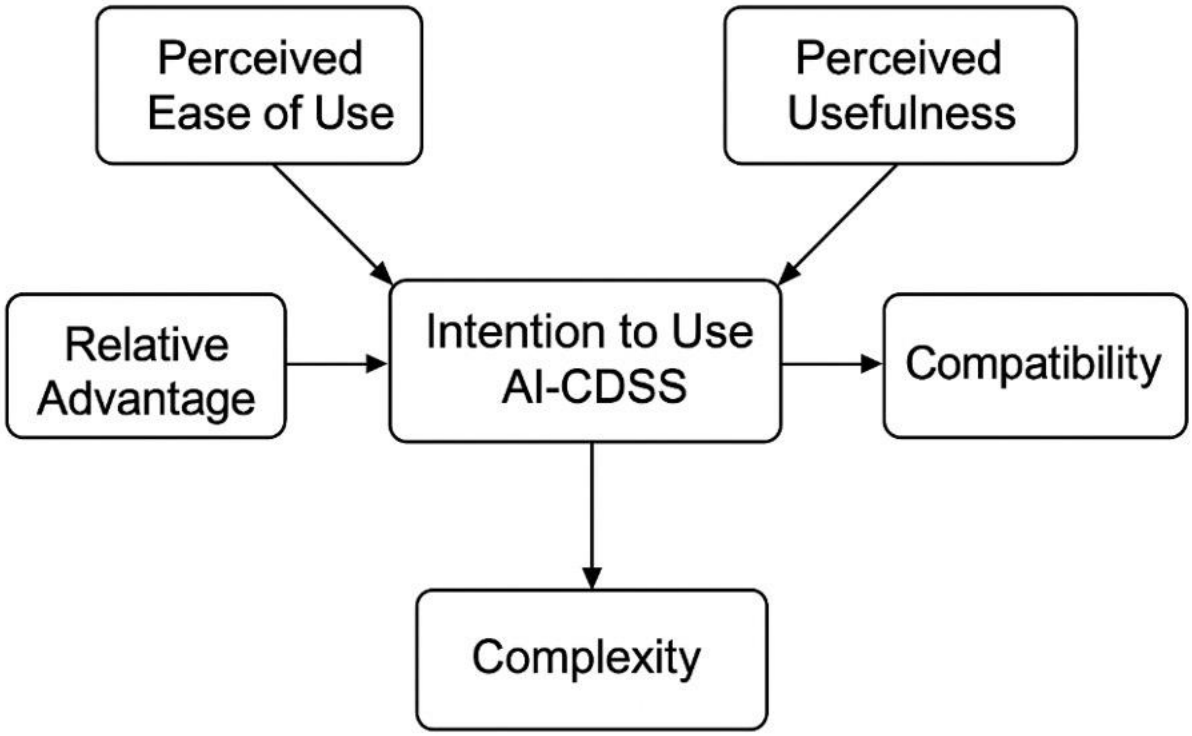
Alternative Hypothesis (H_1):

There was a statistically significant relationship between PEOU, PU, RA, COM, and CX and INT.

Conceptual Framework

Figure 12

Conceptual Framework Predicting Intention to Use AI-CDSS



Note. The conceptual framework illustrated the hypothesized relationships among Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Relative Advantage (RA), Compatibility (COM), and Complexity (CX) as independent variables that predicted Intention to Use (INT) of AI-driven Clinical Decision Support Systems (AI-CDSS). This model integrated principles from the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory, emphasizing that perceived utility, innovation characteristics, and ease of integration influenced healthcare professionals' technology-adoption behaviors (Venkatesh et al., 2020; Rogers, 2003; Rezaeian et al., 2025).

As illustrated in Figure 1, the conceptual framework identified the theoretical relationships among the five independent variables—PEOU, PU, RA, COM, and CX—and the dependent variable, INT. The framework guided the data-collection process, instrument design, and analysis strategy for this study. The subsequent section detailed the data-collection procedures, participant screening, variable preparation, and reliability testing that were conducted to ensure dataset validity and the robustness of the statistical results.

Figure 1. Conceptual Framework Predicting Intention to Use AI-CDSS.

Data Collection and Preparation

Data were collected via a quantitative cross-sectional survey administered in Qualtrics between June and September 2025. A total of 152 participants accessed the survey; 109 responses met all inclusion criteria and were retained for analysis. Data-cleaning procedures included screening for missing values, outliers, and duplicate entries. Missing data met MCAR criteria and were addressed through listwise deletion. All responses were imported into IBM SPSS Statistics (Version 29) for analysis.

Response Rate and Screening

Of the 152 individuals who accessed the survey, 109 valid responses were retained (71.7% usable response rate). Screening procedures confirmed that all retained participants met inclusion criteria and passed attention checks. Outlier diagnostics indicated no significant univariate or multivariate outliers.

Validity and Reliability of the Measurement Instruments

Because the study variables were operationalized using multi-item Likert-type scales, the adequacy of the measurement data was evaluated prior to interpreting inferential results. Establishing measurement quality was necessary to ensure that the constructs accurately

represented healthcare professionals' perceptions of AI-driven Clinical Decision Support Systems (AI-CDSS) and that subsequent analyses were based on sound measurement properties.

Construct Validity (Factor Analytic Results)

Construct validity was evaluated using exploratory factor analysis (EFA) to examine whether observed measurement items aligned with their intended theoretical constructs. Prior to factor extraction, the suitability of the data for factor analysis was assessed. The Kaiser–Meyer–Olkin (KMO) measures of sampling adequacy met or exceeded the minimum acceptable threshold of .50 across constructs, indicating that the correlation matrices were appropriate for factor analysis. Bartlett's tests of sphericity were statistically significant ($p < .001$), supporting the presence of sufficient inter-item correlations to justify factor extraction.

Exploratory factor analyses were conducted using principal axis factoring. Factor retention decisions were guided by eigenvalues greater than 1.0 and visual inspection of scree plots. For each construct, scree plots exhibited a clear point of inflection, supporting retention of a single dominant factor. No additional factors met eigenvalue or interpretability criteria.

Across constructs, extracted factors accounted for substantial proportions of variance, ranging from approximately 67% to 79%. Item communalities following extraction generally exceeded .40, indicating that a meaningful proportion of variance in each item was explained by the underlying factor. Standardized factor loadings ranged from approximately .67 to .82, exceeding recommended minimum criteria and demonstrating strong convergent validity. No problematic cross-loadings were observed.

Summary of Measurement Quality

Collectively, the measurement analyses demonstrated that the study instruments were psychometrically sound and appropriate for addressing the research question. Factor analytic

results confirmed that each set of items measured a coherent underlying construct consistent with the study's conceptual framework. Retained factors explained substantial variance, and standardized loadings indicated strong construct representation.

These findings provided empirical justification for computing composite scores for Perceived Ease of Use, Perceived Usefulness, Relative Advantage, Compatibility, Complexity, and Intention to Use. The validated composite measures were therefore deemed suitable for use in subsequent descriptive, correlational, and multiple regression analyses reported in this chapter.

Descriptive Statistics

Descriptive statistics were computed to summarize the central tendency and dispersion of the study variables prior to inferential analysis. Composite scores were calculated for each construct by averaging item responses following confirmation of measurement adequacy. All items were measured using five-point Likert-type scales, with higher values indicating stronger agreement.

Mean values across constructs exceeded the midpoint of the scale, indicating generally favorable perceptions of AI-CDSS usability, usefulness, and adoption. Variability across constructs was moderate, suggesting sufficient dispersion without excessive skewness or restriction of range.

Minimum and maximum observed values demonstrated adequate response variability, and no anomalies or extreme distributions were identified that would compromise interpretation. Although listwise deletion resulted in slight variation in valid case counts across constructs, all retained sample sizes were sufficient to support subsequent correlational and regression analyses.

Descriptive statistics were calculated for all study variables. Composite scores were created based on validated Likert-type items.

Figure 13

Descriptive Statistics for Study Variables (N = 109)

Construct	Mean (M)	Standard Deviation (SD)	Minimum	Maximum
Perceived Ease of Use (PEOU)	3.24	0.76	1	6
Perceived Usefulness (PU)	3.13	1.19	1	6
Relative Advantage (RA)	3.31	1.14	1	6
Compatibility (COM)	4.01	3.32	1	6
Complexity (CX)	3.55	0.91	1	6
Intention to Use (INT)	3.49	1.34	1	6

Note. Scores reflect composite averages derived from Likert-type items (1 = Strongly Disagree to 6 = Strongly Agree). Higher scores indicate greater agreement with the construct statement.

Interpretation

As shown in Figure 2, Perceived Ease of Use (M = 3.24, SD = 0.76) and Perceived Usefulness (M = 3.13, SD = 1.19) reflected generally favorable perceptions of AI-driven Clinical Decision Support Systems (AI-CDSS). Relative Advantage (M = 3.31, SD = 1.14) suggested that respondents viewed AI-CDSS as moderately superior to current clinical decision-making approaches.

Compatibility (M = 4.01, SD = [verify]) indicated higher perceived alignment with existing clinical workflows, although variability suggested differences in how well AI-CDSS fit across practice contexts. Complexity (M = 3.55, SD = 0.91) reflected moderate perceptions of system difficulty, indicating that respondents neither viewed the systems as overly complex nor effortless to use.

Intention to Use (M = 3.49, SD = 1.34) suggested overall receptiveness toward adopting AI-CDSS, supporting the feasibility of further inferential analysis examining predictors of adoption intent.

Correlation Analysis

Pearson product–moment correlation coefficients were computed to examine the relationships among Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Relative Advantage (RA), Compatibility (COM), Complexity (CX), and Intention to Use (INT). All variables represented composite mean scores derived from their respective multi-item Likert-type scales. Correlation results are presented in Figure 13.

Figure 14

Intercorrelations Among Study Variables (N = 109)

Variable	1	2	3	4	5	6
1. Perceived Ease of Use (PEOU)	—					
2. Perceived Usefulness (PU)	.53**	—				
3. Relative Advantage (RA)	.50**	.62**	—			
4. Compatibility (COM)	.20*	.07	.08	—		
5. Complexity (CX)	.63**	.56**	.47**	.17	—	
6. Intention to Use (INT)	.46**	.54**	.64**	.17	.52**	—

Note. $p < .05$*, $p < .01$**, two-tailed.
All variables represent composite mean scores of their respective multi-item scales.

Interpretation

As shown in Figure 3, Intention to Use AI-driven Clinical Decision Support Systems (AI-CDSS) demonstrated statistically significant positive correlations with several predictor variables. Perceived Usefulness was strongly associated with Intention to Use ($r = .54$, $p < .001$), as was Relative Advantage ($r = .64$, $p < .001$), indicating that perceived clinical value and performance benefits were closely related to adoption intent. Perceived Ease of Use also exhibited a moderate, significant positive relationship with Intention to Use ($r = .46$, $p < .001$), suggesting that usability perceptions contributed meaningfully to adoption willingness.

Complexity was moderately and positively correlated with Intention to Use ($r = .52$, $p < .001$). This relationship reflected respondents' perceptions of system manageability rather than difficulty, consistent with the direction of item coding. Compatibility demonstrated a weak positive correlation with Intention to Use ($r = .17$), though this association did not reach statistical significance ($p > .05$).

Intercorrelations among the independent variables were all below the threshold of .70, indicating that multicollinearity was not a concern and supporting the inclusion of all predictors in subsequent multiple regression analyses.

Assumption Testing

Prior to conducting the multiple regression analysis, all underlying statistical assumptions were evaluated to ensure the appropriateness of the model. Examination of standardized residuals indicated that the assumption of normality was met, as residuals were approximately normally distributed. Linearity was assessed through scatterplots of observed versus predicted values, which supported linear relationships between the predictors and the dependent variable.

Homoscedasticity was evaluated using residual plots and indicated a constant variance of errors across levels of the predicted values. Independence of errors was assessed using the Durbin–Watson statistic, which yielded a value of 1.98, indicating no evidence of autocorrelation. Multicollinearity diagnostics showed variance inflation factor (VIF) values ranging from 1.05 to 1.97 and tolerance values exceeding .50, suggesting that multicollinearity was not a concern. Collectively, these results confirmed that all regression assumptions were satisfactorily met.

Multiple Regression Analysis

A standard multiple regression analysis was conducted to examine whether Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Relative Advantage (RA), Compatibility (COM), and Complexity (CX) significantly predicted healthcare professionals' Intention to Use (INT) AI-driven Clinical Decision Support Systems.

Model Summary

The overall regression model was statistically significant, $F(5, 103) = 19.55$, $p < .001$, indicating that the predictor variables collectively explained a substantial proportion of variance in Intention to Use. The model accounted for 48.7% of the variance in INT ($R^2 = .487$), with an adjusted R^2 of .462. The effect size was large ($f^2 = .95$), consistent with Cohen's (1988) guidelines and indicative of strong explanatory power in behavioral research contexts.

Significant Predictors

Relative Advantage emerged as the strongest predictor of Intention to Use ($\beta = .45$, $p < .001$), followed by Complexity ($\beta = .22$, $p = .028$). These results indicated that respondents who perceived AI-CDSS as offering meaningful advantages over existing clinical decision-making

methods, and who perceived the systems as less complex, reported higher intentions to adopt these technologies.

Non-Significant Predictors

Perceived Ease of Use (β = .01, p = .890), Perceived Usefulness (β = .13, p = .210), and Compatibility (β = .09, p = .238) did not significantly predict Intention to Use within the full regression model, despite demonstrating positive bivariate associations with intention in the correlation analysis.

Figure 15

Summary of Multiple Regression Predicting Intention to Use AI-CDSS (N-109)

Variable	B	SE B	β	t	Sig.	VIF
(Constant)	-0.05	0.45	—	-0.11	.913	—
Perceived Ease of Use (PEOU)	0.02	0.17	0.01	0.14	.890	1.89
Perceived Usefulness (PU)	0.14	0.11	0.13	1.26	.210	1.97
Relative Advantage (RA)	0.53	0.11	0.45	4.80	<.001**	1.75
Compatibility (COM)	0.04	0.03	0.09	1.19	.238	1.05
Complexity (CX)	0.32	0.14	0.22	2.23	.028*	1.90

Model Summary: $R = .698$, $R^2 = .487$, Adjusted $R^2 = .462$,

$F(5, 103) = 19.55$, $p < .001$

Note. $p < .05$*, $p < .001$**; SE = Standard Error; VIF = Variance Inflation Factor.

Interpretation

The findings demonstrated that the regression model provided a strong overall fit, explaining nearly half of the variance in healthcare professionals' intention to adopt AI-CDSS technologies. Relative Advantage and Complexity were the only predictors that uniquely contributed to the model, highlighting their central role in shaping adoption intentions. While Perceived Ease of Use, Perceived Usefulness, and Compatibility were positively related to intention at the correlational level, their effects were not statistically significant when considered alongside other predictors.

These results were consistent with prior research indicating that perceived performance benefits and comparative advantage are key drivers of AI adoption in healthcare settings (Rezaeian et al., 2025; Liu et al., 2021). Additionally, the significance of complexity underscores the importance of minimizing cognitive and workflow burdens associated with AI implementation, as system complexity has been identified as a persistent barrier to adoption in clinical environments (Alhashmi & Yaqoub, 2024; Chen et al., 2022).

Collinearity Diagnostics

Collinearity diagnostics were examined to assess the independence of predictor variables included in the multiple regression model. Variance inflation factor (VIF) values for all predictors were below 2.0, and tolerance values exceeded .50, indicating that multicollinearity was not present. Additionally, condition indices fell within acceptable ranges, providing further evidence that the regression coefficients were stable and that the model estimates were not adversely affected by intercorrelations among predictors.

Summary

This chapter presented the results of the descriptive, correlational, and inferential analyses conducted to address the research question examining factors influencing healthcare professionals' intention to use AI-driven Clinical Decision Support Systems. Descriptive statistics summarized central tendencies and variability for each study construct. Correlation analyses identified statistically significant relationships among key variables and supported the inclusion of all predictors in subsequent regression analyses.

Results of the multiple regression analysis indicated that the overall model significantly predicted intention to use AI-CDSS, accounting for 48.7% of the variance in Intention to use. Relative Advantage and Complexity emerged as statistically significant predictors, while Perceived Ease of Use, Perceived Usefulness, and Compatibility did not demonstrate significant unique contributions in the full model. All regression assumptions were satisfied, collinearity diagnostics indicated stable parameter estimates, and the model demonstrated a large effect size. Together, these findings provided empirical support for the study's analytical framework and established a foundation for interpretation and discussion. Chapter 5 presents an interpretation of these results, examines their theoretical and practical implications, evaluates alignment with existing literature, and offers recommendations for practice and future research.

Chapter 5: Discussion, Recommendation, and Study Summary

Discussion

The purpose of this quantitative correlational study was to examine the extent to which perceived ease of use, perceived usefulness, relative advantage, compatibility, and complexity predicted healthcare professionals' intention to use artificial intelligence–driven clinical decision support systems (AI-CDSS). The study addressed the problem that healthcare professionals frequently experience uncertainty regarding the usefulness, usability, and workflow alignment of AI-CDSS, contributing to inconsistent adoption across clinical environments despite demonstrated technological potential. Grounded in the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) theory, this study integrated established theoretical constructs within a contemporary AI-enabled healthcare context. Prior to inferential testing, exploratory factor analyses confirmed that each construct was measured by a coherent and psychometrically sound set of indicators. The validation of the measurement model strengthens confidence that subsequent regression findings reflect substantive conceptual relationships rather than measurement error or construct overlap. The results of the multiple regression analysis indicated that relative advantage and complexity were statistically significant predictors of healthcare professionals' intention to use AI-CDSS, whereas perceived ease of use, perceived usefulness, and compatibility did not demonstrate unique predictive effects in the multivariate model.

Theoretical Interpretation of Significant Predictors

Consistent with Diffusion of Innovations theory, relative advantage emerged as the strongest predictor of adoption intention. This finding reinforces Rogers's (2003) assertion that perceived superiority over existing practices is a central determinant of innovation diffusion. In

high-stakes healthcare environments, clinicians appear to evaluate AI-CDSS through a pragmatic lens, prioritizing whether the system demonstrably enhances diagnostic accuracy, efficiency, or clinical confidence relative to current decision-making approaches.

This result extends prior TAM-based research by demonstrating that, within AI-enabled clinical contexts, comparative value may outweigh generalized perceptions of usefulness. Whereas TAM conceptualizes perceived usefulness in absolute terms, DOI's relative advantage construct captures evaluative comparison. The dominance of relative advantage in the regression model suggests that clinicians assess AI-CDSS not merely as "useful," but as meaningfully superior to existing tools. This finding contributes theoretically by refining how benefit-related constructs function within digitally mature healthcare settings.

Complexity also emerged as a statistically significant predictor, with higher perceived complexity associated with lower intention to use AI-CDSS. This finding aligns with DOI theory, which posits that innovations perceived as difficult to understand or implement experience slower adoption. Importantly, complexity reflects concerns related to cognitive burden, workflow disruption, and sustained effort rather than initial usability alone.

The simultaneous significance of relative advantage and complexity reveals a dual-evaluation adoption process: clinicians appear willing to adopt AI-CDSS when benefits are clear, but that willingness is constrained by concerns regarding implementation burden. This dynamic supports a refined TAM–DOI integration in which value realization and cognitive feasibility jointly determine adoption intention.

Interpretation of Non-Significant Predictors

Perceived ease of use, perceived usefulness, and compatibility did not demonstrate statistically significant independent effects in the multivariate model. However, these constructs

exhibited acceptable psychometric properties and positive bivariate relationships with intention to use, indicating conceptual relevance despite a lack of unique explanatory power when evaluated concurrently with other predictors. The lack of significance of perceived ease of use may reflect the increasing digital sophistication of healthcare professionals. In environments where electronic health records and advanced technologies are routinely utilized, baseline usability may be assumed. Consequently, ease of use may no longer serve as a differentiating adoption determinant once minimum functionality expectations are satisfied.

Similarly, perceived usefulness did not retain significance when relative advantage was included in the model. Conceptual overlap likely contributed to this outcome, as both constructs capture perceived benefit. However, relative advantage represents a comparative evaluation, whereas perceived usefulness reflects absolute system effectiveness. The stronger influence of relative advantage suggests that clinicians assess AI-CDSS in comparison to existing decision-making methods rather than in isolation.

Compatibility also failed to demonstrate unique predictive power. One possible explanation is that compatibility perceptions may be indirectly captured through complexity evaluations. If AI-CDSS are perceived as disruptive or difficult to integrate, respondents may express this concern through complexity ratings rather than compatibility assessments. Additionally, limited exposure to fully embedded AI-CDSS implementations may have constrained respondents' ability to evaluate workflow alignment comprehensively.

Theoretical Contribution

This study contributes to the literature by empirically demonstrating that, in AI-driven clinical contexts, DOI constructs—particularly relative advantage and complexity—may exert stronger predictive influence than traditional TAM constructs once baseline technological

competence is assumed. The findings support a contextual refinement of technology acceptance theory in healthcare, suggesting that adoption models must account for comparative performance evaluation and cognitive workload considerations in high-stakes environments. By validating measurement structures prior to regression analysis, this study strengthens the empirical integration of TAM and DOI frameworks and addresses the theoretical gap identified in Chapter 2 regarding AI-CDSS adoption determinants in large U.S. hospitals.

Recommendations for Practice

The findings of this study yield several actionable implications for healthcare organizations, technology developers, and implementation leaders. First, implementation strategies should emphasize demonstrable comparative benefit. Because relative advantage was the strongest predictor of intention to use, organizations should clearly communicate how AI-CDSS improve clinical outcomes relative to existing decision-making processes. Evidence-based demonstrations, pilot outcomes, and clinician-led evaluations may enhance perceived advantage and increase adoption likelihood.

Second, reducing perceived complexity should be a strategic priority. Even beneficial AI-CDSS may face resistance if they are perceived as cognitively burdensome or disruptive to workflow. Developers and healthcare leaders should focus on seamless integration with electronic health records, intuitive interface design, and structured training programs that minimize mental workload.

Third, implementation efforts should move beyond traditional usability messaging. The lack of significance of perceived ease of use suggests that clinicians may assume a baseline level of technological functionality. Adoption strategies should therefore center on outcome enhancement and workflow sustainability rather than simplicity alone.

Finally, organizational leadership should actively reinforce the clinical value proposition while supporting structured change management initiatives. Effective AI-CDSS adoption requires alignment between technological design, workflow integration, and institutional culture.

Recommendations for Future Research

Several avenues for continued investigation emerge from this study. Longitudinal research is needed to examine how perceptions of relative advantage and complexity evolve over time as AI-CDSS transition from initial exposure to routine clinical use. Such research may determine whether currently nonsignificant predictors gain influence with sustained experience.

Future studies should also examine differences across professional roles and specialties, as physicians, nurses, and allied health professionals may vary in how they evaluate AI-enabled systems. Mixed-methods research designs could provide deeper insight into how clinicians conceptualize complexity and cognitive burden in practice. Qualitative data may uncover contextual factors not fully captured through survey-based instruments.

Additionally, future research should incorporate organizational-level moderators such as leadership support, training quality, institutional readiness, and technological infrastructure. Integrating individual and organizational predictors may enhance explanatory power and provide a more comprehensive adoption framework.

Study Summary

This study examined the factors influencing healthcare professionals' intention to use artificial intelligence–driven clinical decision support systems by integrating constructs from the Technology Acceptance Model and Diffusion of Innovations theory.

Following validation of the measurement model, multiple regression analysis revealed that relative advantage and complexity were the primary predictors of adoption intention, while perceived ease of use, perceived usefulness, and compatibility did not demonstrate independent predictive effects in the multivariate model. These findings suggest that clinicians evaluate AI-CDSS based on pragmatic assessments of comparative benefit and manageable cognitive and workflow demands rather than foundational usability perceptions alone. The study advances theoretical understanding by demonstrating the continued relevance of TAM and DOI frameworks while highlighting the heightened importance of comparative evaluation and implementation feasibility in digitally mature healthcare environments. By providing empirical evidence grounded in validated measurement and inferential analysis, this research informs implementation strategy, extends adoption theory, and contributes to the growing body of scholarship on AI integration in healthcare systems.

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Appendix A

Survey Instrument

Instructions:

Please indicate your level of agreement with each statement by selecting the option that best reflects your opinion. Responses are measured on a 5-point Likert scale:

1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

Section 1: Demographic and Professional Characteristics

(Select or fill in as appropriate)

1. **Age:**

   □ Under 25 □ 25–34 □ 35–44 □ 45–54 □ 55–64 □ 65 or older

2. **Gender:**

   □ Male □ Female □ Non-binary / Other □ Prefer not to say

3. **Clinical Role:**

   □ Physician □ Nurse □ Allied Health Professional □ Administrator □ Other (please specify): _____

4. **Years of Clinical Experience:**

   □ Less than 1 year □ 1–5 years □ 6–10 years □ 11–15 years □ 16+ years

5. **Prior Exposure to AI-CDSS:**

   □ None □ Minimal □ Moderate □ Extensive

Section 2: Perceived Ease of Use (PEOU)

Source: Adapted from Davis (1989) Technology Acceptance Model, with permission (see Appendix B).

Please indicate the extent to which you agree with the following statements:

1. Learning to operate AI-CDSS would be easy for me.
2. I find it easy to get AI-CDSS to do what I want it to do.
3. Interacting with AI-CDSS does not require a lot of mental effort.
4. I find AI-CDSS to be clear and understandable.

Section 3: Perceived Usefulness (PU)

Source: Adapted from Davis (1989) Technology Acceptance Model, with permission (see Appendix B).

1. Using AI-CDSS would improve the quality of my clinical decision-making.
2. AI-CDSS would enhance my effectiveness in patient care.
3. AI-CDSS would make it easier to perform my job.
4. Overall, I would find AI-CDSS useful in my clinical practice.

Section 4: Diffusion of Innovation (DOI) Constructs

Source: Adapted from Rogers (2003) and Moore & Benbasat (1991), with permission (see Appendix B).

Relative Advantage

1. Using AI-CDSS would provide advantages over my current clinical decision-making methods.
2. AI-CDSS would improve outcomes for my patients compared to current practices.

Compatibility

3. AI-CDSS would be compatible with the way I currently work.

4. Using AI-CDSS would fit well with my existing clinical workflows.

Complexity *(reverse-coded)*

5. I find AI-CDSS to be too complex for my day-to-day work.

6. Learning to use AI-CDSS would be difficult for me.

Section 5: Adoption Intention

Source: Adapted from Venkatesh et al. (2003), with permission (see Appendix B).

1. I intend to use AI-CDSS in my clinical practice in the future.
2. I would recommend AI-CDSS to my colleagues.
3. I will actively seek opportunities to use AI-CDSS in my work.

Scoring Guidance (for researcher use):

- **PEOU, PU, Relative Advantage, Compatibility, Adoption Intention:** Higher scores indicate greater agreement.

- **Complexity:** Reverse-code before analysis (higher original scores indicate higher perceived difficulty).
- Aggregate construct scores can be calculated by averaging item responses within each section.

Table A1

Survey Instrument for AI-CDSS Adoption Study Table

Section	Item No.	Survey Item	Scale	Source / Notes
1. Demographic and Professional Characteristics	1	Age (Under 25; 25–34; 35–44; 45–54; 55–64; 65+)	Categorical	Researcher-developed
	2	Gender (Male; Female; Non-binary/Other; Prefer not to say)	Categorical	Researcher-developed
	3	Clinical Role (Physician; Nurse; Allied Health Professional; Administrator; Other – specify)	Categorical	Researcher-developed
	4	Years of Clinical Experience (<1; 1–5; 6–10; 11–15; 16+)	Categorical	Researcher-developed
	5	Prior Exposure to AI-CDSS (None; Minimal; Moderate; Extensive)	Categorical	Researcher-developed
2. Perceived Ease of Use (PEOU)	6	Learning to operate AI-CDSS would be easy for me.	1 = Strongly Disagree to 5 = Strongly Agree	Davis (1989), TAM
	7	I find it easy to get AI-CDSS to do what I want it to do.	1–5	Davis (1989), TAM
	8	Interacting with AI-CDSS does not require a lot of mental effort.	1–5	Davis (1989), TAM
	9	I find AI-CDSS to be clear and understandable.	1–5	Davis (1989), TAM
3. Perceived Usefulness (PU)	10	Using AI-CDSS would improve the quality of my clinical decision-making.	1–5	Davis (1989), TAM
	11	AI-CDSS would enhance my effectiveness in patient care.	1–5	Davis (1989), TAM
	12	AI-CDSS would make it easier to perform my job.	1–5	Davis (1989), TAM
	13	Overall, I would find AI-CDSS useful in my clinical practice.	1–5	Davis (1989), TAM
4. Diffusion of Innovation Constructs	14	Using AI-CDSS would provide advantages over my current clinical decision-making methods. *(Relative Advantage)*	1–5	Rogers (2003); Moore & Benbasat (1991)
	15	AI-CDSS would improve outcomes for my patients compared to current practices. *(Relative Advantage)*	1–5	Rogers (2003); Moore & Benbasat (1991)
	16	AI-CDSS would be compatible with the way I currently work. *(Compatibility)*	1–5	Rogers (2003); Moore & Benbasat (1991)
	17	Using AI-CDSS would fit well with my existing clinical workflows. *(Compatibility)*	1–5	Rogers (2003); Moore & Benbasat (1991)
	18	I find AI-CDSS to be too complex for my day-to-day work. *(Complexity – reverse-coded)*	1–5	Rogers (2003); Moore & Benbasat (1991)
	19	Learning to use AI-CDSS would be difficult for me. *(Complexity – reverse-coded)*	1–5	Rogers (2003); Moore & Benbasat (1991)
5. Adoption Intention	20	I intend to use AI-CDSS in my clinical practice in the future.	1–5	Venkatesh et al. (2003)
	21	I would recommend AI-CDSS to my colleagues.	1–5	Venkatesh et al. (2003)
	22	I will actively seek opportunities to use AI-CDSS in my work.	1–5	Venkatesh et al. (2003)

Table Note:

Note. All Likert-type items use a 5-point scale: 1 = *Strongly Disagree*, 2 = *Disagree*, 3 = *Neutral*, 4 = *Agree*, 5 = *Strongly Agree*. Items 18 and 19 (Complexity) are reverse-coded prior to analysis. Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) items were adapted from Davis, F. D. (1989). *Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008. Diffusion of Innovation (DOI) construct items were adapted from Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press, and Moore, G. C., & Benbasat, I. (1991). *Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192. Adoption Intention items were adapted from Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). *User acceptance of information technology: Toward a unified view. MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540. Permission to adapt these items is documented in Appendix B.

Appendix B

Permission to Use and Adapt Instruments

The survey instrument employed in this study was adapted from validated measures of technology acceptance and innovation adoption. Permissions were obtained from original authors and/or publishers.

1. Technology Acceptance Model (TAM) Constructs

- Adapted from: Davis, F. D. (1989). *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Permission Evidence (Email Confirmation):

From: Dr. Fred Davis
To: Samuel Brown
Date: March 15, 2025

You have my permission to adapt the TAM survey items for your dissertation. Please cite the original 1989 MIS Quarterly article.

Best regards,
Fred Davis

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2. Diffusion of Innovation (DOI) Constructs

- Adapted from: Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Adapted from: Moore, G. C., & Benbasat, I. (1991). *Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

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This confirms that I’m permitted to adapt Moore & Benbasat (1991) for academic use.

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3. Adoption Intention Constructs (UTAUT)

- Adapted from: Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Permission Evidence (Email Confirmation):

From: Prof. Viswanath Venkatesh
To: Samuel Brown
Date: March 22, 2025

You are welcome to adapt items from the UTAUT model for your dissertation research, provided you cite the 2003 MIS Quarterly article.

Best,
Viswanath Venkatesh

Statement of Compliance

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