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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR DIABETES PREDICTION AND MANAGEMENT: STRENGTHENING AI-DRIVEN HEALTHCARE INNOVATION AND BIG DATA SECURITY WITHIN THE U.S. PUBLIC HEALTH INFRASTRUCTURE

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Abstract

This study addresses the challenge of ensuring that artificial intelligence and machine learning for diabetes prediction and management are deployed within secure big data environments in the U.S. public health infrastructure. The purpose is to quantify how AI and machine learning adoption, big data security practices, healthcare innovation, and trust in AI systems jointly predict diabetes management effectiveness in cloud and enterprise settings. A quantitative cross sectional, case-based survey design was applied to 285 professionals from 18 U.S. healthcare organizations operating EHR and analytics platforms on enterprise or cloud infrastructures. Key latent variables were AI or machine learning adoption for diabetes, big data security, healthcare innovation, trust in AI, and diabetes management effectiveness, all measured on five-point Likert scales and analyzed using descriptive statistics, correlations, and multiple regression with moderation. AI and machine learning adoption showed a strong positive association with diabetes management effectiveness ($r = .52$, $p < .001$; $\beta = .29$, $p < .001$) and healthcare innovation ($r = .63$, $p < .001$; $\beta = .63$, $p < .001$). Big data security strongly predicted trust in AI ($r = .57$, $p < .001$; $\beta = .57$, $p < .001$) and significantly moderated the adoption effect on effectiveness (interaction $\beta = .14$, $\Delta R^2 = .02$, $p = .005$). The full regression model explained 60 percent of the variance in diabetes management effectiveness ($R^2 = .60$), demonstrating that secure and trusted AI enabled environments are critical for translating predictive and decision support tools into tangible improvements in population-oriented diabetes care.

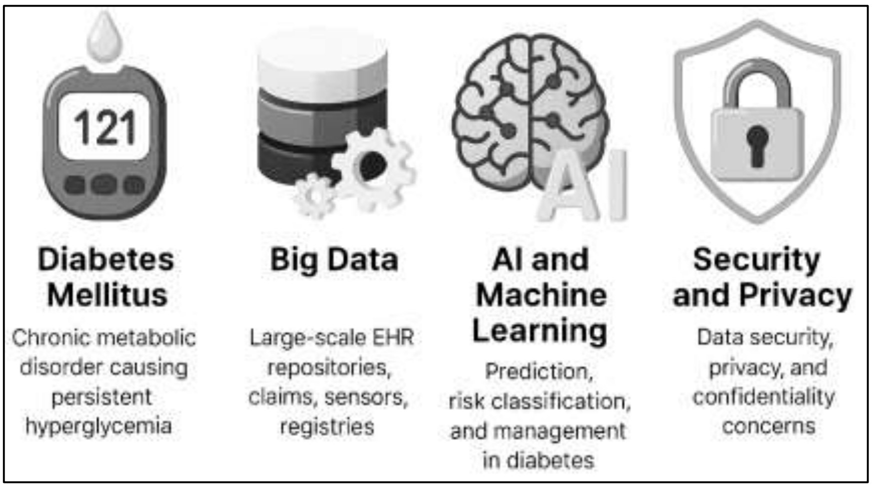
Keywords

Artificial Intelligence; Machine Learning; Diabetes Management; Big Data Security; Healthcare Innovation;

INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder characterized by persistent hyperglycemia resulting from defects in insulin secretion, insulin action, or both, and it is recognized globally as a major non-communicable disease burden with significant clinical and economic consequences (Saeedi et al., 2019). Estimates from the International Diabetes Federation indicate that more than 460 million adults were living with diabetes in 2019, with projections suggesting substantial growth by 2030 and 2045, emphasizing the strain on health systems worldwide (Saeedi et al., 2019). The United States represents one of the most affected countries, where diabetes-related morbidity, mortality, and expenditures create sustained pressure on public health infrastructure and safety-net providers. Within this context, digital health technologies, electronic health records (EHRs), and large-scale administrative and clinical datasets have become central assets for public health surveillance, risk stratification, and chronic disease management (Raghupathi & Raghupathi, 2014). Big data analytics in healthcare is generally defined as the use of high-volume, high-velocity, and high-variety data—drawn from EHRs, claims, sensors, and registries—to generate insights that can support decision-making at patient, provider, and system levels (Khanra et al., 2020). In public health practice, these analytic capacities increasingly intersect with artificial intelligence (AI) and machine learning (ML), which are broadly understood as computational approaches that enable systems to learn patterns from data and make predictions or recommendations without being explicitly programmed for each decision rule (Contreras & Vehi, 2018).

Figure 1: Interaction of Diabetes Mellitus within U.S. Public Health Systems



Over the past two decades, AI and ML methods have been extensively applied to diabetes prediction and risk classification, using demographic, clinical, laboratory, and behavioral variables to identify individuals at high risk of type 2 diabetes (T2D) or poor glycemic outcomes. Systematic reviews show that supervised learning algorithms such as logistic regression, random forests, support vector machines, and gradient boosting, as well as deep learning architectures, have achieved high predictive performance for incident T2D and diabetes-related complications when trained on large epidemiological or EHR-based datasets (Fregoso-Aparicio et al., 2021). These models often outperform traditional risk scores by capturing complex, non-linear relationships among predictors such as body mass index, age, family history, lipid profile, and lifestyle indicators (Deberneh & Kim, 2021) Reviews summarizing current AI applications in diabetes note rapid growth in model development, including ensemble and deep-learning approaches that leverage multi-modal data from laboratory results, claims, wearable devices, and clinical notes (Atkinson & et al., 2021). At the same time, comparative studies highlight variability in model calibration, external validity, and real-world integration into care pathways, particularly when algorithms are transported across health systems or demographic groups (Contreras & Vehi, 2018). These observations position AI- and ML-based diabetes prediction as a promising yet methodologically heterogeneous domain closely linked to the quality, representativeness, and governance of underlying big data assets.

Beyond prediction, AI-driven tools are increasingly embedded in diabetes management workflows, supporting tasks such as insulin titration, glycemic pattern interpretation, decision support for clinicians, and self-management support for patients. A growing body of work demonstrates that AI-based clinical decision support systems (CDSSs) can emulate expert endocrinologist recommendations for insulin dosing and glycemic control using continuous glucose monitoring (CGM) data, structured EHR variables, and historical treatment responses (Nimri et al., 2020). Real-world and trial-based evidence suggests that such systems can improve glycemic metrics—including reductions in HbA1c and increased time in range—without elevating hypoglycemia risk, particularly when integrated into virtual or hybrid care models (Okafor, 2022). Parallel advances in smart devices and smartphone-based technologies connect AI analytics to patients' daily self-management by leveraging sensors, CGM, and mobile applications for feedback and behavior change support (Mărginean & et al., 2022) Systematic reviews of smart-device–enabled diabetes interventions report that technology-assisted self-management, when combined with data-driven feedback or algorithmic recommendations, is frequently associated with improved glycemic control, adherence, and lifestyle behaviors (Aleppo et al., 2023). Telehealth-based diabetes programs that incorporate CGM analytics, remote endocrinology consultation, and structured education illustrate how AI/ML analytics can be embedded within broader care delivery models, with reported reductions in HbA1c and improved time in range in U.S. cohorts (Gal et al., 2020).

The growth of AI- and ML-enabled diabetes tools depends fundamentally on the availability and quality of big data infrastructure in healthcare and public health systems. Big data in healthcare encompasses large-scale EHR repositories, claims databases, disease registries, sensor and device data, and social and environmental datasets, all of which are used to characterize populations, monitor disease patterns, and support decisions at multiple levels (Bonoto et al., 2020). Reviews of big data analytics in healthcare emphasize applications in risk prediction, readmission reduction, pharmacovigilance, and resource planning, noting that machine learning methods are particularly suited for extracting patterns from high-dimensional clinical data (Khanra et al., 2020). At the policy level, big data analytics are increasingly discussed as tools for evidence-informed health policy cycles, enabling surveillance of chronic conditions, evaluation of interventions, and monitoring of performance indicators in near real time (Salas-Vega et al., 2015). For diabetes, these infrastructures support population-level registries, integrated EHR data marts, and quality improvement programs that track care processes and outcomes across large health systems and geographic regions (Keshta & Odeh, 2021). In the U.S., public health agencies and health systems increasingly rely on interoperable data platforms and health information exchanges to integrate laboratory reports, claims, and EHR encounters for chronic disease surveillance, which creates a fertile environment for embedding AI/ML-based diabetes prediction and management tools within broader public health infrastructure (Langer & et al., 2020).

At the same time, the expansion of big data and AI in healthcare intensifies longstanding concerns regarding data security, privacy, confidentiality, and ethical stewardship of personal health information. Large-scale health datasets aggregate highly sensitive attributes including diagnoses, medication histories, biometric measures, and behavioral indicators; breaches or misuse can lead to financial, social, and clinical harms for individuals and communities (Abouelmehdi et al., 2018). Reviews of big healthcare data security describe threats such as unauthorized access, insider misuse, ransomware, and linkage attacks that exploit cross-dataset integration, highlighting technical, organizational, and legal challenges for secure data management (Soni et al., 2017). Studies focusing specifically on EHR security and privacy identify issues related to authentication, access control, encryption, and auditability, as well as socio-technical factors such as user practices and governance structures (Keshta & Odeh, 2021). These analyses underline that the same characteristics that make healthcare big data valuable for AI applications—volume, velocity, and variety—also amplify attack surfaces and complicate compliance with privacy principles such as data minimization and purpose limitation (Majithia et al., 2020). For AI-based diabetes systems operating on integrated EHR and device data, robust security and privacy safeguards become tightly coupled with patient trust, model acceptance, and the willingness of organizations to share or pool data within national or regional public health infrastructures (Keshta & Odeh, 2021).

The U.S. healthcare and public health context illustrates both the opportunities and vulnerabilities inherent in AI-driven, data-intensive infrastructures. Federal incentives for EHR adoption and health information exchange have enabled widespread digitization of clinical records, which supply inputs for AI models and big data analytics (Pichardo-Lowden et al., 2021). At the same time, analyses of cyber incidents and sector-wide challenges describe healthcare organizations as frequent targets of ransomware, phishing, and other cyberattacks, with implications for care continuity, financial stability, and public confidence (Pichardo-Lowden et al., 2022). Studies of U.S. hospital and regional responses to cyber threats underscore the operational complexity of maintaining service delivery during major incidents, including the need for coordinated regional response, redundancy, and recovery strategies for EHR and ancillary systems (Chao et al., 2023). Within this environment, diabetes care increasingly depends on connected devices, cloud-based data platforms, and virtual care models; secure operation of these socio-technical systems affects not only individual patient outcomes but also broader public health functions such as chronic disease surveillance and quality reporting (Aleppo et al., 2023). Evidence from clinical decision support implementations for inpatient and outpatient diabetes care suggests that EHR-integrated tools can modify clinical processes and resource use across institutions, which ties algorithm performance to the reliability and integrity of underlying information systems (Ristevski & Chen, 2018).

Within the specific domain of diabetes, AI-enabled interventions have been developed and evaluated at multiple levels of the care continuum—from individual self-management to specialty clinics and hospital environments—drawing intensively on big data generated by U.S. health systems. Virtual endocrinology clinics and CGM-centric telehealth programs have been implemented using large-scale data streams for remote monitoring and algorithmic feedback, leading to improved glycemic indices and patient-reported outcomes across diverse adult populations (Gal et al., 2020). Randomized and observational studies of virtual diabetes clinics and AI-assisted decision support systems report significant reductions in HbA1c and increased time in range, reflecting the capacity of integrated data platforms to support continuous, data-driven decision-making (Nimri et al., 2020). Reviews of smartphone-based and smart device–enabled interventions for diabetes self-management indicate that mobile health (mHealth) technologies increasingly rely on AI/ML algorithms to tailor feedback, predict glycemic excursions, and guide lifestyle modifications, again leveraging large volumes of longitudinal patient data (Mărginean & et al., 2022). These developments position AI and ML as integral components of data-driven diabetes care ecosystems, where prediction, monitoring, and management are tightly linked to the structure and governance of health data infrastructures. That linkage is particularly salient in public health settings, where AI-based diabetes tools must align with population-level surveillance, program evaluation, and health equity objectives supported by national and state data systems (Chao et al., 2023).

Although AI and ML applications for diabetes prediction and management are expanding rapidly, the literature addressing their integration with big data security and governance frameworks within U.S. public health infrastructure is comparatively limited. Existing AI studies frequently focus on algorithm development and performance metrics such as area under the curve, sensitivity, and specificity, using de-identified or single-institution datasets, with relatively less emphasis on how models operate within multi-institutional data-sharing arrangements or public health surveillance platforms (Fregoso-Aparicio et al., 2021). Meanwhile, research on big data security and EHR privacy typically treats AI or predictive analytics only as one of many secondary uses of health data, without systematically examining how security controls, breach histories, or regulatory obligations shape the design and deployment of diabetes-specific AI solutions (Aladwani & Almotairi, 2023). In parallel, work on big data–driven health policy and public health decision-making emphasizes the strategic potential of analytics for chronic disease control, while giving comparatively less detailed attention to disease-specific AI workflows combining prediction, clinical decision support, and security-sensitive data flows (Salas-Vega et al., 2015). These strands of literature collectively indicate a complex landscape in which AI-enabled diabetes prediction and management, big data analytics, and data security policies intersect across clinical and public health domains, and they provide the empirical and conceptual grounding for examining how AI-driven healthcare innovation and big data security co-exist within the U.S. public health infrastructure for diabetes(Zou et al., 2018).

In line with this context, the present study is structured around a set of clear, measurable objectives that guide the empirical investigation of artificial intelligence and machine learning for diabetes prediction and management within the U.S. public health infrastructure. The overarching objective is to quantitatively examine how AI- and ML-enabled systems for diabetes prediction and management, together with big data security practices, relate to healthcare innovation and diabetes management effectiveness in selected public health and healthcare organizations. Building on this overall aim, the first specific objective is to assess the current level of AI and machine learning adoption for diabetes prediction and management, including the extent to which predictive models, decision support tools, and data-driven monitoring solutions are implemented and integrated into clinical and public health workflows. A second objective is to evaluate perceived diabetes management effectiveness in organizations that employ AI- and ML-based tools, focusing on self-reported improvements in risk identification, glycemic control, care coordination, and operational efficiency. A third objective is to examine the relationship between AI/ML adoption and healthcare innovation, investigating whether organizations that report higher use of AI and machine learning for diabetes also report more innovative practices, models of care, and digital transformation in diabetes services. A fourth objective is to analyze how big data security practices, including technical, organizational, and procedural safeguards, are associated with stakeholders' trust in AI-driven diabetes systems and their willingness to rely on data-intensive tools for decision-making. A fifth objective is to develop and test a regression model in which AI/ML adoption, big data security practices, healthcare innovation, and trust in AI systems act as predictors of diabetes management effectiveness, using survey-based Likert measures and quantitative analysis. To support these objectives, the study adopts a cross-sectional, case-study–based quantitative design that uses descriptive statistics to profile the sample, correlation analysis to examine bivariate relationships, and multiple regression modeling to identify statistically significant predictors and their relative contributions. Through this objective-oriented structure, the research provides a coherent basis for empirical testing of the proposed relationships and for systematically addressing the research questions and hypotheses formulated in the introductory section.

LITERATURE REVIEW

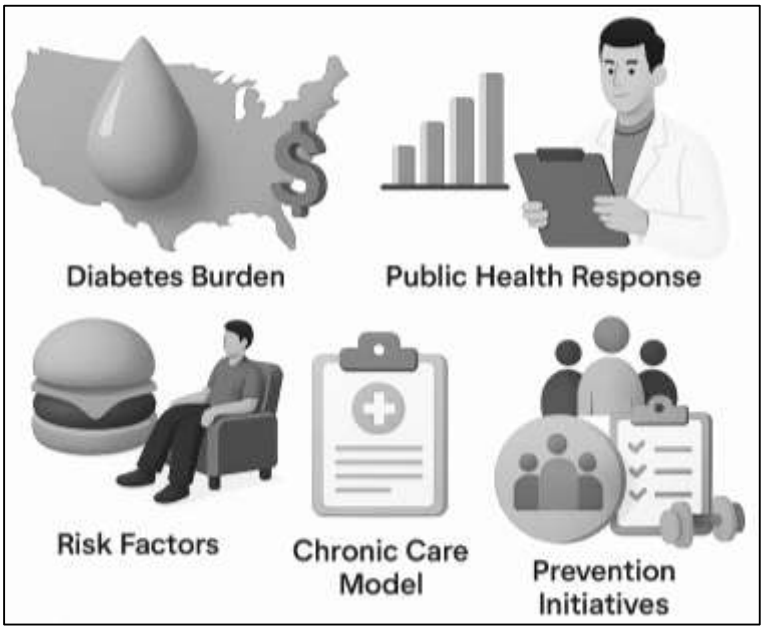
The literature on artificial intelligence, machine learning, and big data in healthcare has expanded rapidly in the past two decades, creating an essential foundation for understanding how these technologies can transform diabetes prediction and management within complex health systems. Diabetes has long been recognized as a data-intensive condition, requiring continuous monitoring of glycemic patterns, treatment regimens, comorbidities, and lifestyle factors; the digitization of health records, proliferation of connected devices, and growth of large-scale clinical and administrative databases have dramatically increased the volume and granularity of data available to clinicians, researchers, and public health agencies. Within this environment, AI and ML techniques have been applied to tasks such as early risk stratification, complication prediction, optimization of insulin therapy, and personalization of self-management support, while big data infrastructures have enabled the aggregation and linkage of information across care settings, populations, and time. However, the integration of these technologies into routine practice does not occur in a vacuum: it is shaped by organizational readiness, regulatory frameworks, data governance models, and evolving expectations concerning privacy, security, and trust. A comprehensive literature review for this study therefore needs to move beyond isolated algorithmic performance reports and consider AI- and ML-enabled diabetes tools as components of broader socio-technical systems embedded in national public health infrastructures. This requires attention to several interrelated strands of research, including epidemiological and public health perspectives on the diabetes burden; technical and clinical evidence on AI and ML approaches for prediction and management; work on big data architectures, interoperability, and analytics in healthcare; studies of information security, privacy protection, and cyber risk in health data environments; and organizational and theoretical perspectives on innovation and technology adoption in clinical and public health settings. By synthesizing findings across these domains and then narrowing to a conceptual and theoretical framework that explicitly links AI/ML adoption, big data security practices, healthcare innovation, trust, and diabetes management effectiveness, the literature review will provide the analytical foundation for the study's research questions, hypotheses, and empirical model.

Diabetes and Public Health Response in the United States

The burden of diabetes in the United States has escalated into a major public health crisis, with implications that extend far beyond individual morbidity and mortality to encompass health system performance, economic stability, and social equity. National cost-of-illness analyses estimate that diagnosed diabetes accounts for hundreds of billions of dollars annually in direct medical spending and productivity losses, consuming roughly one in every four health care dollars and more than doubling average expenditures for affected individuals compared with those without diabetes (Association, 2018). These aggregate figures translate into everyday realities in which people living with diabetes experience higher rates of hospitalizations, emergency visits, disability, and premature death, often in the context of multiple coexisting conditions such as cardiovascular disease, chronic kidney disease, and obesity (Arfan et al., 2021; Ara, 2021). At the same time, diabetes prevalence continues to climb, driven by aging populations, sedentary lifestyles, unhealthy food environments, and structural determinants such as neighborhood deprivation, racism, food insecurity, and limited access to preventive and primary care. State-level analyses show that the economic burden is not distributed evenly; some states incur per-person diabetes costs that are nearly twice those of others, reflecting regional differences in risk factor profiles, health care infrastructure, insurance coverage, and investment in prevention and chronic disease management (Jahid, 2021; Akbar & Farzana, 2021; Shrestha et al., 2018). These disparities are mirrored in patterns of incidence, complications, and mortality, with low-income communities and racial and ethnic minority populations bearing a disproportionate share of the burden. Consequently, diabetes has become a sentinel indicator of how well the U.S. public health infrastructure anticipates, monitors, and responds to chronic, data-intensive health threats. Taken together, these trends underscore that diabetes is not only a clinical condition managed within exam rooms but also a systems-level problem shaped by policies, environments, and intersectoral resource allocation decisions that either mitigate or amplify risk across populations.

In response, U.S. public health and healthcare stakeholders have increasingly reframed diabetes as a chronic condition that demands coordinated, population-based management rather than fragmented, episodic care (Reza et al., 2021; Saikat, 2021). One influential framework, the Chronic Care Model, emphasizes reorganizing primary care around proactive, planned interactions, self-management support, clinical information systems, decision support, and community linkages; systematic reviews of its application in U.S. primary care settings indicate that multi-component, team-based interventions grounded in this model can improve glycemic control, adherence to evidence-based guidelines, and use of diabetes self-management education services (Shaikh & Aditya, 2021; Stellefson et al., 2013; Kanti & Shaikat, 2021). In practice, this has encouraged primary care practices and health systems to build registries that track key indicators such as HbA1c, blood pressure, lipids, and screening for microvascular complications, and to use these data for outreach to high-risk patients who might otherwise fall through the cracks. The model also highlights the importance of empowering patients through structured education, collaborative goal setting, and culturally relevant self-management tools, delivered by multidisciplinary teams that can include nurses, pharmacists, dietitians, diabetes educators, and community health workers. From a public health perspective, the Chronic Care Model provides a conceptual bridge between clinical encounters and broader community resources, suggesting that effective diabetes control requires linkages to programs that promote physical activity, healthy eating, tobacco cessation, and stress management (Ariful & Ara, 2022; Arman & Kamrul, 2022). Importantly, this perspective reframes patients as active partners whose experiences and preferences should shape care pathways and priorities. This shift also creates new expectations for data interoperability and performance measurement, as payers and regulators increasingly tie incentives to documented improvements in chronic disease outcomes at the population level (Mesbaul & Farabe, 2022; Nahid, 2022). By positioning diabetes care within a chronic care and population health framework, these initiatives move beyond narrow biometric targets toward a more comprehensive view of quality, equity, and long-term risk reduction that is consistent with contemporary visions of learning health systems.

Figure 2: Key Components of the Diabetes Burden Framework in the United States

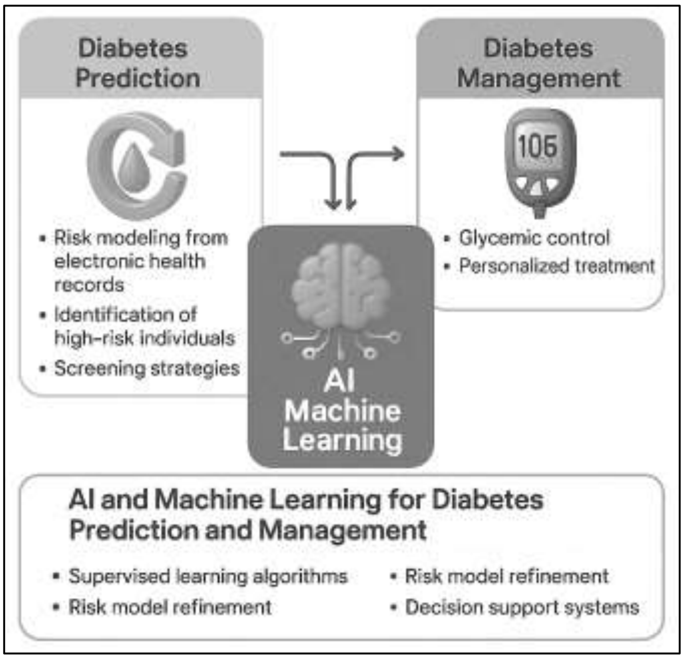


At the national level, the public health response has been strengthened by the development and scaling of structured prevention initiatives, particularly for individuals with prediabetes. The U.S. National Diabetes Prevention Program (NDPP), coordinated by the Centers for Disease Control and Prevention, translates the intensive lifestyle intervention originally tested in the Diabetes Prevention Program clinical trial into community, primary care, and digital delivery models, with thousands of recognized sites using standardized curricula and performance reporting to deliver weight-loss and behavior-change interventions at scale (Gruss et al., 2019; Hossain & Milon, 2022; Abdur & Haider, 2022). Program participants typically engage in group-based or virtual sessions focused on nutrition, physical activity, and problem solving, with the goal of achieving sustained modest weight loss and increased exercise, supported by trained lifestyle coaches. Evaluations of this and related efforts highlight both successes—such as documented risk reduction among completers, expanding insurance coverage, and growing experience with culturally tailored delivery—and persistent challenges, including limited reach into high-burden communities, high attrition, workforce shortages, and uneven capacity for implementation in under-resourced rural and urban settings (Mushfequr & Praveen, 2022; Mortuza & Rauf, 2022). Recent syntheses argue that meeting the full scope of the diabetes epidemic will require not only further diffusion of evidence-based prevention and management interventions but also stronger alignment of policies, payment reforms, and cross-sector collaborations to close gaps in diagnosis, treatment, and prevention across the life course (Herman & Schillinger, 2023; Rakibul & Samia, 2022; Rony & Ashraful, 2022). For health systems and public agencies, these developments create an imperative and an opportunity to integrate advanced analytics with established prevention platforms to target resources where the burden is greatest. Within this context, the present study's focus on artificial intelligence–enabled prediction and management of diabetes—embedded in the realities of U.S. public health infrastructure and big data security—builds directly on an evolving body of work that treats diabetes as a population-level challenge requiring coordinated, multi-level public health action in diverse real-world settings.

AI and Machine Learning for Diabetes Prediction and Management

Machine learning and artificial intelligence have become central methodological pillars in contemporary diabetes research, particularly as health systems accumulate increasingly large and heterogeneous datasets (Saikat, 2022; Shaikh & Sudipto, 2022). Early syntheses of the field showed that techniques such as logistic regression, decision trees, support vector machines, Bayesian networks, and ensemble classifiers were applied across a wide range of diabetes-related problems, including disease onset prediction, complication risk stratification, treatment optimization, and pattern discovery in self-monitoring data (Abdul, 2023; Abdulla & Zaman, 2023; Kavakiotis et al., 2017).

Figure 3: Integration of AI and Machine Learning Diabetes Prediction



These reviews emphasized that diabetes is unusually well suited to data-driven modeling because it is monitored through routinely collected clinical indicators, longitudinal laboratory values, medication histories, and lifestyle variables that can be transformed into structured features for supervised and unsupervised learning (Arfan et al., 2023; Ara & Onyinyechi, 2023). They also argued that the growing availability of genomic, sensor, and imaging data further expands the representational space in which computational models can detect subtle signals related to metabolic dysfunction and future complication risk (Kavakiotis et al., 2017; Amin & Mesbaul, 2023; Foysal & Aditya, 2023). At the same time, the literature stressed that model performance is tightly linked to data quality, feature engineering, and choices about evaluation metrics, noting that apparently high accuracies in small or highly selected samples may not generalize to population-based settings or to the complex realities of routine care (Hamidur, 2023; Rashid et al., 2023). Together, these methodological reflections positioned AI and machine learning as powerful but context-sensitive tools, whose contribution to diabetes care depends on thoughtful integration with clinical expertise, transparent reporting of performance, and iterative validation across diverse health-system environments rather than on isolated demonstrations of technical feasibility (Musfiqur & Kamrul, 2023; Muzahidul & Mohaiminul, 2023). In addition, early overviews highlighted unresolved questions about interpretability, fairness, and potential automation bias, arguing that algorithm development must be accompanied by attention to how models will be understood by clinicians and patients, how error will be distributed across subgroups, and how responsibility for decision-making will be shared between human and machine actors in diabetes care (Amin & Praveen, 2023; Hasan & Ashraful, 2023).

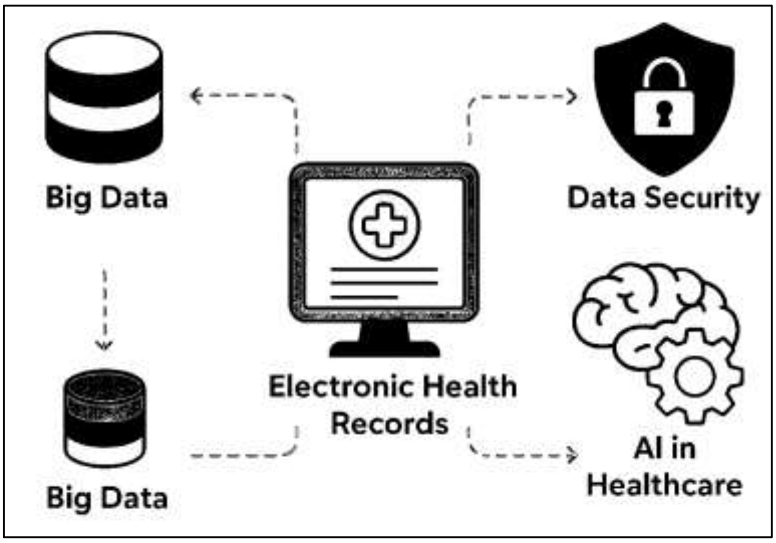
Within the domain of diabetes prediction, several empirical studies have leveraged electronic health records to construct risk models that identify individuals with undiagnosed diabetes or those at high risk of developing type 2 diabetes. One influential investigation presented a machine-learning framework to identify type 2 diabetes cases from routine EHR data, demonstrating that algorithms combining demographic variables, diagnostic codes, medications, and laboratory results could substantially improve case-finding compared with rule-based phenotyping strategies or reliance on diagnostic codes alone (Ibne & Kamrul, 2023; Mushfequr & Ashraful, 2023; Zheng et al., 2017). The authors showed that supervised learning models trained on heterogeneous data sources were able to capture complex, non-linear relations among predictors and to flag probable cases that traditional rules missed, thereby illustrating how algorithmic approaches can extend the reach of case surveillance in health-system datasets (Pankaz Roy & Kamrul, 2023; Saba et al., 2023). Building on this line of work, a retrospective cohort analysis evaluated multiple machine-learning algorithms for predicting incident type 2 diabetes, reporting that ensemble models such as random forests and gradient boosting achieved superior discrimination compared with conventional risk scores when supplied with systematically selected clinical and demographic variables (Mao et al., 2022; Saba & Kanti, 2023; Shaikh & Farabe, 2023). The study highlighted that combining epidemiologic variable selection with machine-learning techniques can yield risk models with satisfactory accuracy and potential for implementation in preventive care. Complementary evidence from risk-factor–oriented modeling in a lower-resource setting has further shown that machine-learning pipelines with dual feature-selection strategies can isolate a parsimonious set of clinical, dietary, and lifestyle predictors that jointly produce high discrimination for type 2 diabetes, while revealing context-specific risk patterns that might be obscured in purely clinical models (Kakoly et al., 2023). Taken together, these contributions show how AI and machine learning can operationalize high-dimensional data to support earlier identification of high-risk individuals, better understanding of risk-factor interactions, and more rational screening strategies. This predictive focus directly informs screening strategies and allocation of limited preventive resources.

AI and machine-learning techniques have also been increasingly applied to the active management of diabetes after diagnosis, particularly in relation to glycemic control, treatment titration, and personalization of therapy in routine practice. Recent proof-of-concept work has demonstrated that artificial-intelligence–based decision support systems can ingest high-quality EHR data and generate insulin dosage recommendations for people with type 2 diabetes, implemented within hospital information systems and evaluated in clinical care (Abdul & Shoeb, 2024; Chen et al., 2023; Zamal Haider & Hozyfa, 2023). In that study, a machine-learning model trained on treatment patterns and glucose outcomes was embedded into a clinical workflow to assist clinicians with basal insulin titration, and results indicated that AI-assisted titration could achieve glycemic control comparable to specialist care while potentially reducing workload and standardizing practice across providers (AUddin, et al., 2024; Alam, Sohel, et al., 2024). When viewed alongside predictive models for diabetes onset and risk-factor profiling, such decision support systems illustrate how insights derived from longitudinal datasets can be translated into point-of-care recommendations that adapt to individual patients' evolving clinical states (Hozyfa & Shahrin, 2024; Hasan & Shah, 2024). The same methodological advances that enhance prediction—including feature selection, ensemble learning, and continual model updating—can be repurposed to refine treatment algorithms, recommend dose adjustments, and anticipate trajectories of glycemic control under alternative therapeutic scenarios (Hasan & Zayadul, 2024; Muzahidul & Aditya, 2024). These management-focused applications draw attention to the operational conditions under which AI tools must function, such as timeliness of data feeds, integration with clinician workflows, usability of interfaces, and availability of safeguards for monitoring recommendation quality and detecting model drift. Experience from these projects feeds into discussions about how AI-enabled systems can contribute to learning health systems, in which outcome data are cycled back into analytic pipelines to refine diabetes care strategies at patient and population levels (Hasan & Rakibul, 2024; Mominul, 2024). In this way, the literature on AI-supported management complements the prediction-oriented evidence base, showing that machine-learning methods can support a continuum of functions from early risk detection to dynamic treatment adjustment within data-rich health-system infrastructures.

Big Data, Electronic Health Records in AI-Driven Healthcare

Big data has emerged as a defining feature of contemporary health systems, capturing the massive, complex and rapidly generated digital traces of clinical care, administration, and patient self-management (Mominul & Zaki, 2024; Roy & Sai Praveen, 2024). In contrast to traditional, small-scale datasets, big health care data are typically described in terms of high volume, velocity and variety, encompassing structured elements such as diagnosis codes and laboratory values, semi-structured feeds from devices, and unstructured clinical narratives, images and signals that must be transformed before they can be analyzed meaningfully (Belle et al., 2015; Rony & Hozyfa, 2024; Saba & Hasan, 2024). Within this landscape, electronic health records (EHRs) function as a central data spine: they consolidate encounters, medications, test results and problem lists across time, and they increasingly integrate data from registries, claims systems and personal health technologies, creating longitudinal records at the level of individual patients and populations (Shaikat & Zaman, 2024; Sudipto & Hasan, 2024; White, 2014). Health care organizations in the United States and other high-income settings have invested heavily in EHR platforms and ancillary data warehouses to support billing, reporting and quality measurement, but these infrastructures simultaneously generate rich data resources that can be repurposed for clinical research, public health surveillance and artificial intelligence (AI)–enabled analytics (Kruse et al., 2016; Kanti & Saba, 2024; Kanti & Praveen, 2024). As a result, discussions of big data in health care now routinely treat EHR-derived datasets as core assets for population risk prediction, stratified care management and learning health systems, where routine data flows are analyzed and fed back to decision-makers in near real time (Belle et al., 2015; Haider & Praveen, 2024; Zulqarnain & Zayadul, 2024). At the same time, the integration of data from multiple institutional and regional sources exposes longstanding problems of data standardization, missingness and bias, highlighting the need for robust data governance frameworks that balance secondary use for analytics with obligations to maintain accuracy, relevance and accountability across the life cycle of health information (Majumder, 2025; Ara, 2025; White, 2014).

Figure 4: Data Ecosystem Linking Big Data for AI in Healthcare



Methodological work on the use of EHR-based big data emphasizes both the scientific opportunities and the operational challenges that arise when these routinely collected data are used for analytics, predictive modeling and evaluation (Habibullah, 2025; Hozyfa & Ashraful, 2025). From an epidemiologic and health services research perspective, large-scale clinical databases offer unprecedented statistical power, diversity of patient populations and the ability to capture care processes and outcomes as they occur in real-world practice, including settings that are underrepresented in traditional clinical trials (Asfaquar, 2025; Foysal, 2025; Shortreed et al., 2019). However, because EHRs were designed primarily for documentation and billing rather than research, investigators must contend with issues such as inconsistent coding practices, variable data completeness across sites and time, and the need to reconcile information from multiple care venues and information systems into coherent patient-level histories (Majadul Islam & Abdur, 2025; Mohaiminul, 2025; White, 2014). These challenges have given rise to extensive work on data curation pipelines, phenotyping algorithms and analytic methods that can accommodate censoring, time-varying confounding and complex missing-data patterns in observational health care datasets (Mominul, 2025; Muzahidul, 2025; Shortreed et al., 2019). At the system level, conceptualizations of learning health systems position EHR-linked data hubs as engines of continuous improvement, where data are extracted from clinical workflows, transformed into actionable knowledge through analytic and AI techniques, and then reintegrated as updated guidelines, decision support tools or performance dashboards for clinicians and managers (Belle et al., 2015; Hossain, 2025; Zaman, 2025). Realizing this vision requires not only technical capacity to store and process large volumes of heterogeneous data, but also organizational capabilities for cross-disciplinary collaboration, governance mechanisms for prioritizing analytic questions, and feedback infrastructures that translate model outputs into changes in care processes and population health strategies (Kruse et al., 2016; Akbar & Sharmin, 2025; Hasan, 2025). In large, multi-institution networks, additional complexity arises from interoperability limitations and heterogeneous local configurations of EHR systems, which can constrain the portability of AI models and require harmonization layers that reconcile divergent data schemas before meaningful cross-site analyses are possible (Ibne, 2025; Milon, 2025; Shortreed et al., 2019).

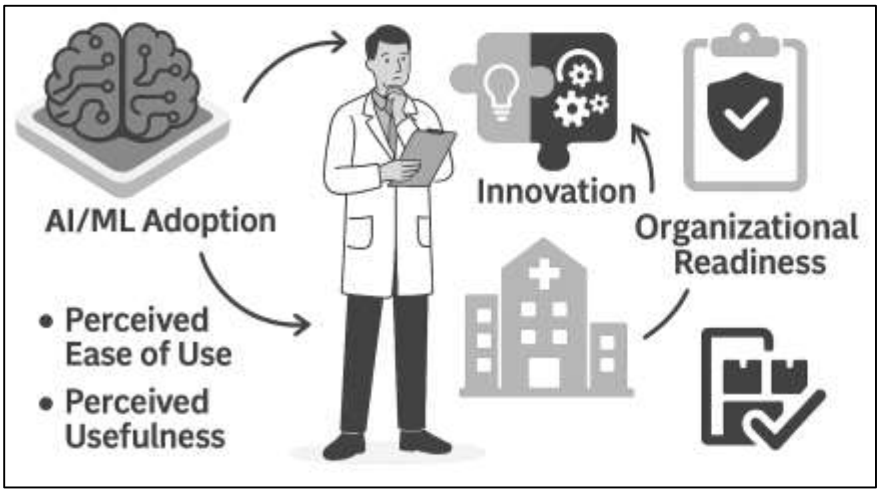
Alongside these opportunities, a parallel stream of scholarship examines the security and privacy implications of EHR-based big data, emphasizing that the sensitivity of health information and the scale of contemporary data repositories significantly elevate the consequences of unauthorized access, misuse or loss (Farabe, 2025; Kamrul, 2025). Systematic reviews of EHR security and privacy describe a broad range of threats, including external attacks, insider misuse and accidental disclosures, and they catalog technical safeguards such as encryption, digital signatures, audit logs and fine-grained access control as essential building blocks of trustworthy health information infrastructures (Fernández-Alemán et al., 2013; Mushfequr, 2025; Shahrin, 2025). At the same time, these reviews highlight that compliance with regulations and standards alone is insufficient; security controls must be integrated with organizational policies, user training and incident response capabilities in order to maintain the confidentiality, integrity and availability of EHR data over time (Fernández-Alemán et al., 2013; Rakibul, 2025; Saba, 2025). Work at the intersection of big data analytics and governance further argues that information governance frameworks must explicitly address how privacy, consent and data-minimization principles are operationalized when EHR data are repurposed for secondary uses such as AI model development, quality improvement and population health surveillance (Kruse et al., 2016; Praveen, 2025; Saikat, 2025). Authors in this domain stress that big data initiatives should incorporate privacy-by-design principles, role-based access management and rigorous de-identification or pseudonymization procedures, while also acknowledging that complete anonymization may be difficult to guarantee in the presence of high-dimensional, linkable datasets (Shaikat, 2025; Shaikh, 2025; White, 2014). In practice, this means that organizations seeking to leverage EHR-based big data for AI-driven diabetes prediction and management must simultaneously invest in the technical and socio-organizational components of security, cultivating a culture of shared responsibility in which clinicians, data scientists, information technology teams and leaders jointly steward health data as both a strategic asset and a protected public trust (Shortreed et al., 2019; Kanti, 2025; Waladur & Hasan, 2025).

AI/ML Adoption and Organizational Readiness in Healthcare

The literature on health information technology adoption has consistently emphasized that the successful introduction of new digital tools, including artificial intelligence and machine learning applications, depends not only on technical performance but also on how clinicians and managers perceive and respond to these technologies. Early work adapting social–psychological models of technology use to healthcare, most notably the Technology Acceptance Model, argued that end users' behavioral intention to use a system is largely shaped by perceptions of its usefulness for improving job performance and its ease of use in daily workflows (Holden & Karsh, 2010; Haider, 2025). These theoretical perspectives are particularly relevant for AI-enabled diabetes prediction and management tools, which promise to provide decision support, risk scores and automated recommendations but may also be experienced as opaque, disruptive or misaligned with professional judgement (Alam, Nabil, Uddin, et al., 2024). Empirical work with front-line clinicians demonstrates that perceived ease of use and perceived usefulness are strongly associated with behavioral intention to use electronic health records, highlighting that even relatively mature technologies can face adoption barriers if they are seen as cumbersome or poorly aligned with clinical workflows (Alam, Sohel, et al., 2024; Tubaishat, 2017). Studies of technology acceptance in healthcare suggest that clinicians are more likely to embrace advanced digital tools when they perceive clear advantages for patient care, when interfaces are intuitive and integrated into existing documentation systems, and when training and support reduce the cognitive effort required to interpret system outputs (Sohel et al., 2022). Conversely, perceived threats to clinical autonomy, concerns about reliability and medicolegal responsibility, and experiences of increased documentation burden can erode perceived usefulness and ease of use, thereby reducing adoption even when technologies are technically sound (Tahosin et al., 2025). In this sense, conceptual models of acceptance provide a lens for understanding why similar AI or decision-support tools may be enthusiastically adopted in some diabetes care settings yet remain underused or resisted in others, despite comparable technical capabilities and infrastructure investments (Alam, Sohel, et al., 2024; Alam et al., 2023).

Studies that examine the day-to-day realities of implementing clinical decision support and other digital tools provide additional insight into how organizational and individual factors interact to shape technology adoption (Alam et al., 2024; Fokhrul & Fardaus, 2022). Systematic reviews of clinical decision support system adoption highlight a recurring set of barriers, including inadequate integration with existing workflows, poor usability, excessive alert burden, lack of clinician trust in the underlying evidence or logic, and insufficient training and technical support (Alam & Alam, 2022; Devaraj et al., 2014). These reviews also identify facilitators such as visible leadership commitment, involvement of end users in design and configuration, iterative refinement based on feedback, and alignment of decision-support content with local guidelines and performance metrics. When viewed through the lens of AI-enabled diabetes care, these findings suggest that even highly accurate predictive models may fail to influence practice if they are delivered through clumsy interfaces, provide recommendations at the wrong time in the clinical encounter, or are perceived as contradicting established treatment norms.

Figure 5: Factors Influencing AI and Machine Learning Adoption in Healthcare Organizations



At the same time, well-designed implementation strategies that embed AI outputs into familiar workflows, such as pre-visit risk stratification lists, structured order sets or dashboard summaries, can increase the likelihood that clinicians attend to and act on model recommendations. Adoption is also influenced by broader organizational conditions such as staffing levels, competing initiatives and financial pressures, which can limit the capacity of teams to engage with new tools even when they recognize potential benefits (Devaraj et al., 2014). For diabetes-focused AI applications in particular, organizations must consider how predictive outputs will intersect with quality-improvement programs, population health management teams and patient-facing digital tools, ensuring that responsibilities for follow-up, documentation and communication are clearly delineated. Over time, sustained adoption is likely to depend on whether clinicians see tangible improvements in outcomes and workflow efficiency, whether patients perceive added value and fairness in algorithm-supported decisions, and whether governance processes are in place to monitor performance and revise or retire tools that no longer meet clinical or ethical expectations.

Theoretical Framework for AI/ML Adoption in Diabetes Care

The theoretical framework for this study integrates core ideas from technology acceptance, information systems success, information security behavior, and socio-technical implementation research in order to explain how artificial intelligence (AI) and machine-learning (ML) tools for diabetes prediction and management create value within data-intensive public health infrastructures. At the level of individual and organizational adoption, a central pillar is the Technology Acceptance Model (TAM), which proposes that perceived usefulness and perceived ease of use shape users' attitudes and behavioral intention to use a system. A large meta-analysis of TAM found strong, consistent paths from perceived usefulness and ease of use to intention and actual use across a wide variety of information systems, confirming the robustness of the model's core relationships and suggesting that it can be fruitfully extended to emerging technologies such as AI-enabled clinical tools (King & He, 2006). Building on this foundation, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) expands the logic of TAM by incorporating performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit as determinants of behavioral intention and use behavior, particularly in consumer and voluntary-use settings (Venkatesh et al., 2012). For the present research, these perspectives imply that perceived performance benefits of AI/ML models in diabetes care, the effort required to interpret and act on algorithmic recommendations, and perceptions of organizational support will jointly influence the extent to which clinicians and managers accept and routinely use AI-driven diabetes tools. Conceptually, this can be expressed through a behavioral-intention equation of the form

$$BI = \alpha_0 + \alpha_1 PU + \alpha_2 PEOU + \alpha_3 SI + \varepsilon,$$

where BI denotes intention to use AI/ML systems, PU perceived usefulness or performance expectancy, $PEOU$ perceived ease of use or effort expectancy, SI social influence, α_i path coefficients to be estimated, and ε an error term capturing unmeasured influences.

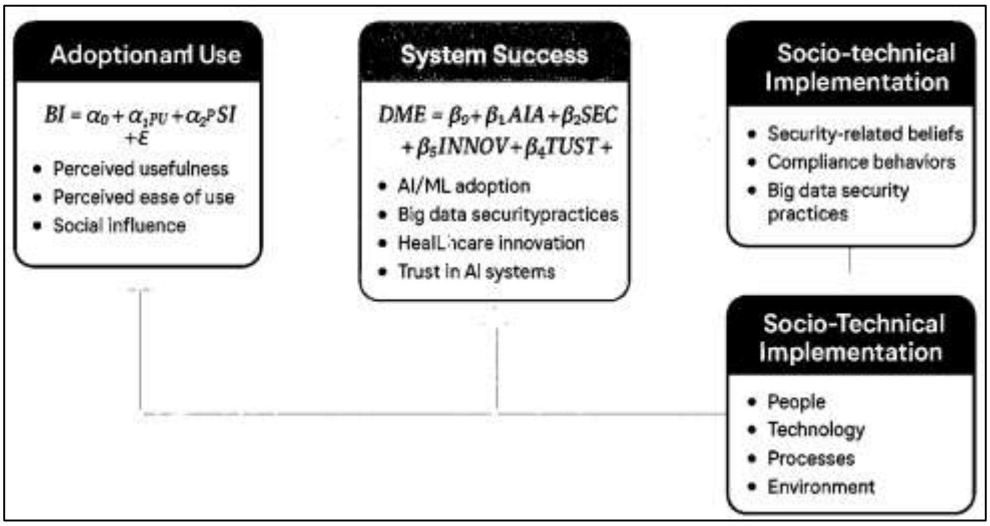
A second strand of the framework focuses on how successful use of AI/ML systems leads to meaningful benefits for individuals, organizations, and public health infrastructures. The DeLone and McLean information systems (IS) success model, as synthesized and extended in later work, identifies system quality, information quality, service quality, use, user satisfaction, and net benefits as interrelated dimensions of IS success, and provides a widely used template for evaluating digital health interventions (Petter et al., 2008). In this study, AI- and ML-based diabetes applications embedded in electronic health record platforms or population health dashboards can be conceptualized as information systems whose technical quality (for example, reliability, speed, and integration), information outputs (for example, accurate, timely, and clinically relevant risk scores), and support services (for example, training and technical assistance) influence patterns of use and satisfaction among clinicians and analysts. Net benefits, in turn, are operationalized as perceived improvements in diabetes management effectiveness, such as earlier identification of high-risk patients, more appropriate treatment decisions, and more efficient allocation of care-management resources. At an empirical level, these relationships motivate a multivariate regression structure in which diabetes management effectiveness (DME) is modelled as a function of AI/ML adoption (AIA), big data security practices (SEC), perceived healthcare innovation ($INNOV$), and trust in AI systems ($TRUST$):

$$DME = \beta_0 + \beta_1 AIA + \beta_2 SEC + \beta_3 INNOV + \beta_4 TRUST + \varepsilon.$$

This formulation links adoption constructs derived from TAM/UTAUT-type models to outcome constructs derived from IS success research, and it aligns with the study's quantitative design, which uses Likert-based measures and regression modelling to test whether higher levels of AI/ML use, stronger security practices, and greater innovation and trust are associated with superior diabetes management outcomes in U.S. public health and healthcare organizations.

The final element of the theoretical framework addresses how security-related beliefs and broader socio-technical conditions shape the implementation and sustainability of AI-enabled diabetes systems in real-world settings. From an information security perspective, models that integrate the Theory of Planned Behavior with Protection Motivation Theory demonstrate that attitudes, subjective norms, perceived behavioral control, response efficacy, self-efficacy, and perceptions of vulnerability and severity jointly influence employees' intentions to comply with information systems security policies (Ifinedo, 2012). In the context of this study, such models support the assumption that big data security practices and staff compliance behaviors are critical antecedents of trust in AI-driven diabetes tools and willingness to share or analyses sensitive health data at scale. At the same time, socio-technical frameworks of technology implementation argue that the fate of health technologies depends on their alignment with the complex, evolving contexts in which they are introduced. The NASSS (Nonadaptation, Abandonment, and challenges to the Scale-up, Spread, and Sustainability) framework, for example, emphasizes how characteristics of the technology, the condition, the value proposition, the adopters, the organization, and the wider system interact over time to shape whether health technologies are successfully mobilized at scale (Greenhalgh et al., 2017). In parallel, cumulative evidence from meta-analytic work on TAM reinforces that the core relationships between beliefs, intentions and use are robust across diverse sectors and applications, providing a stable foundation on which more specialized models such as UTAUT2 and IS success frameworks can be built (King & He, 2006). By combining these perspectives, the present research articulates a multi-level theoretical model in which AI/ML adoption, system success, security and compliance, and socio-technical fit jointly underpin the effectiveness of AI-enabled diabetes prediction and management within the U.S. public health infrastructure, and this integrative framework directly informs the study's hypotheses, survey measures, and regression specifications.

Figure 6: Multilevel Theoretical Framework in AI-Enabled Diabetes Care

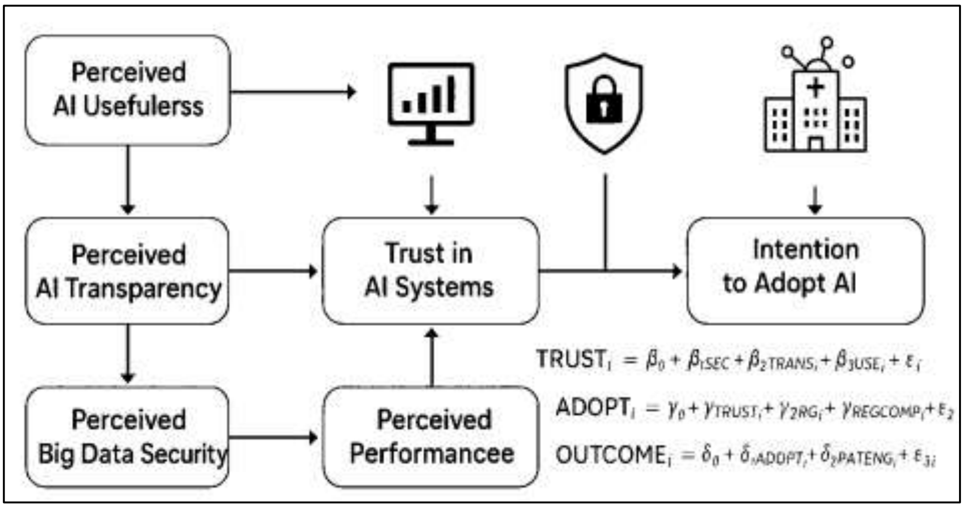


Conceptual Framework and Big Data Security

The conceptual framework for this study synthesizes AI-enabled clinical decision support, big data security, and trust-centered technology adoption within the U.S. public health infrastructure for diabetes prediction and management. In this framework, AI and machine learning solutions for risk stratification, early prediction, and dynamic treatment optimization are embedded within digitally transformed healthcare ecosystems that rely on interoperable data flows and secure analytic platforms. Conceptually, AI in healthcare is not treated as a stand-alone technical artifact but as a socio-technical system in which clinicians, patients, data infrastructures, and institutional policies jointly shape outcomes. Trust is therefore positioned as a relational construct linking technical qualities of AI systems, data governance practices, and user perceptions of safety and reliability in diabetes care (Gille et al., 2020).

Building on evidence-based digital transformation models of the health sector, the framework assumes that AI services for diabetes operate across multiple layers—clinical, organizational, and population health—within a broader architecture of health data platforms and regulatory controls (Konopik & Blunck, 2023). Thus, the framework connects micro-level constructs (e.g., user trust and perceived usefulness) with meso-level factors (organizational support, security culture) and macro-level conditions (data governance and national public health infrastructure).

Figure 7: Multilevel Framework Adoption with Performance in Diabetes Services



At the core of the framework are six primary latent constructs: (a) perceived AI usefulness in diabetes prediction and management, (b) perceived AI transparency and explainability, (c) perceived big data security and privacy protection, (d) trust in AI systems for diabetes care, (e) intention to adopt or rely on AI-driven tools among healthcare professionals and organizational decision-makers, and (f) perceived performance of diabetes services (e.g., timeliness of risk detection, quality of management decisions, and coordination within public health infrastructure). The framework draws on comprehensive conceptualizations of user trust in AI that distinguish antecedents (e.g., competence, reliability, integrity), components (e.g., cognitive and affective trust), and outcomes (e.g., acceptance and continued use) (Yang & Wibowo, 2022). In parallel, foundational trust frameworks conceptualize trust in AI as an interaction among systems—technological, organizational, and social—where transparency, controllability, and alignment with institutional norms determine whether AI is perceived as trustworthy (Lukyanenko et al., 2022). Within diabetes care, these elements converge: clinicians and managers assess whether AI-driven analytics operate on high-quality, securely governed data; whether outputs are intelligible enough to support critical decisions; and whether liability, accountability, and regulatory requirements are clearly allocated across institutions.

The framework is designed to be empirically testable using the quantitative, cross-sectional, case-study–based design and regression modeling specified for this research. At the statistical level, relationships between constructs are expressed through linear regression equations. For example, trust in AI for diabetes care (TRUST_i) for respondent $i$can be modeled as

$$\text{TRUST}_i = \beta_0 + \beta_1 \text{SEC}_i + \beta_2 \text{TRANS}_i + \beta_3 \text{USE}_i + \varepsilon_{1i},$$

where SEC_idenotes perceived data security and privacy, TRANS_iperceived transparency/explainability, and USE_iperceived usefulness of AI-based diabetes tools. Intention to adopt AI-enabled systems (ADOPT_i) is then modeled as

$$\text{ADOPT}_i = \gamma_0 + \gamma_1 \text{TRUST}_i + \gamma_2 \text{ORG}_i + \gamma_3 \text{REGCOMP}_i + \varepsilon_{2i},$$

where ORG_icaptures organizational support and REGCOMP_iperceived regulatory and compliance adequacy. Finally, perceived performance of diabetes services and contribution to public health infrastructure (OUTCOME_i) is expressed as

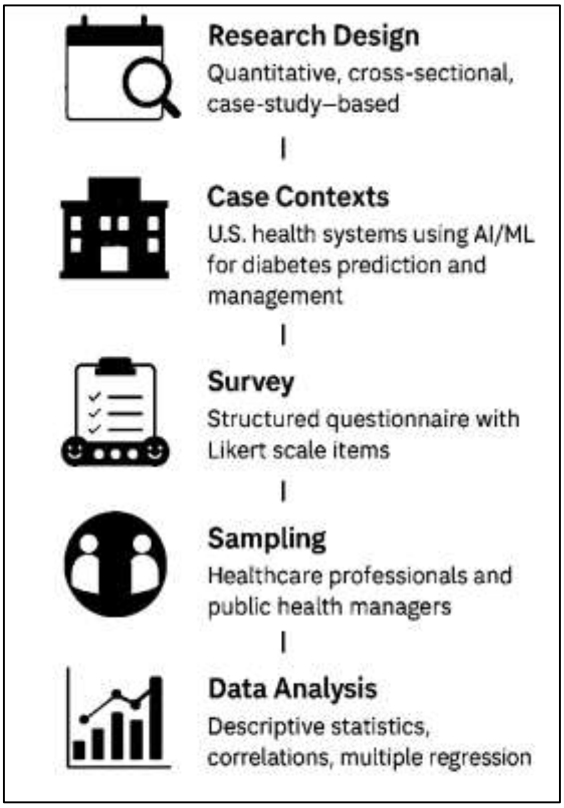
$$\text{OUTCOME}_i = \delta_0 + \delta_1 \text{ADOPT}_i + \delta_2 \text{PATENG}_i + \delta_3 \text{DATAINT}_i + \varepsilon_{3i},$$

where PATENG_irepresents patient engagement with AI-mediated self-management tools and $\text{DATAINT}_i$the level of data integration across public health systems. These linked equations formally encode the conceptual assumption—also emphasized in trust-in-AI and digital transformation literature—that trustworthy, secure, and well-governed AI infrastructures are more likely to be adopted, and that higher adoption in turn contributes to better diabetes prediction, management, and system-level performance in U.S. public health contexts (Asan et al., 2020).

METHOD

The present study has adopted a quantitative, cross-sectional, case-study–based research design to examine how artificial intelligence and machine learning for diabetes prediction and management have been associated with healthcare innovation and big data security within the U.S. public health infrastructure. The design has been chosen because it has allowed the researcher to capture current perceptions and practices at a single point in time across multiple organizations that have already been using or piloting AI- and data-driven diabetes tools. By focusing on real-world health systems and public health entities as case contexts, the study has been positioned to explore AI/ML adoption, data security practices, and diabetes management outcomes as they have actually been experienced in operational environments rather than controlled experimental settings. A structured survey instrument with Likert's five-point scales has been developed and administered to healthcare professionals, IT and data specialists, and public health managers who have been directly involved in diabetes care, analytics, or health information governance. This instrument has been designed to measure key latent constructs such as AI/ML adoption for diabetes prediction and management, perceived big data security and privacy practices, perceived healthcare innovation, trust in AI-driven systems, and perceived diabetes management effectiveness.

Figure 8: Research methodology



The sampling strategy has targeted U.S.-based organizations that have maintained electronic health records and data infrastructures sufficient to support AI- or analytics-enabled diabetes initiatives, thereby ensuring that respondents have been able to comment on concrete tools, policies, and workflows. Data collection procedures have emphasized voluntary participation, informed consent, and protection of respondent anonymity, so that participants have felt able to provide candid assessments of both strengths and weaknesses in current practice. Once collected, the survey data have been prepared and analyzed using descriptive statistics to profile the sample and summarize variable distributions, followed by correlation analysis to explore bivariate relationships among constructs and multiple regression models to test the study's hypotheses. In this way, the methodological approach has been aligned with the study's objective of quantitatively linking AI/ML adoption, big data security, healthcare innovation, trust, and diabetes management effectiveness within U.S. public health and healthcare settings.

Research Design

The study has employed a quantitative, cross-sectional, case-study–based design to investigate how AI and machine learning for diabetes prediction and management have been functioning within U.S. public health and healthcare organizations. This design has been selected because it has enabled the researcher to capture current practices, perceptions, and organizational conditions at a single point in time across multiple real-world settings. The case-study orientation has been used to anchor the investigation in specific organizations that have already implemented, piloted, or seriously planned AI-enabled diabetes initiatives. Within this design, standardized survey measures have been administered so that relationships among key constructs have been examined using statistical techniques rather than qualitative interpretation. The research design has therefore combined breadth, through its multi-site cross-sectional approach, and depth, through its focus on AI- and data-intensive diabetes contexts. Overall, this design has been aligned with the study's objective of testing hypothesized relationships between AI/ML adoption, big data security, innovation, trust, and diabetes management effectiveness.

Sample

The target population for this study has consisted of professionals who have been directly involved in diabetes-related care, analytics, or information governance within U.S. health systems and public health agencies that have maintained digital infrastructures. This population has included physicians, nurses, diabetes educators, clinical pharmacists, data scientists, health IT specialists, and public health managers who have interacted with AI-driven tools or data-intensive processes for diabetes prediction and management. From this population, a non-probability, purposive sample has been drawn, focusing on organizations that have already used or explored AI/ML applications or advanced analytics in diabetes programs. Within each organization, participants have been invited based on their roles and experience with relevant systems, so that respondents have been able to provide informed responses about AI adoption, big data security, and diabetes management outcomes. Planned sample size has been determined to ensure sufficient statistical power for correlation and regression analyses, and recruitment efforts have been aimed at maximizing representation across organizational types and roles.

Instruments

Data have been collected using a structured, self-administered questionnaire that has been specifically designed for this study to capture perceptions of AI/ML adoption, big data security practices, healthcare innovation, trust in AI systems, and diabetes management effectiveness. The instrument has used Likert's five-point scale (ranging from "strongly disagree" to "strongly agree") so that latent constructs have been quantified for statistical analysis. Items have been grouped into logically ordered sections, beginning with demographic and organizational characteristics, followed by scales measuring AI/ML use for diabetes prediction and management, security and privacy safeguards surrounding health data, innovation in diabetes services, trust in AI-driven recommendations, and perceived effectiveness of diabetes management at clinical and population levels. The questionnaire has been formatted for online distribution so that participants have been able to complete it securely and at their convenience. Clear instructions and definitions have been provided to ensure that respondents have interpreted items consistently and have felt confident in their answers.

Data Collection

Data collection has been carried out through an organized series of steps that have ensured ethical conduct, participant convenience, and data quality. Initially, organizational contacts and gatekeepers have been approached to secure permission for recruitment within eligible health systems and public health agencies. Following approval, potential participants have been invited via email, which has contained a brief study description, inclusion criteria, and a secure link to the online questionnaire. The invitation has explained that participation has been voluntary and anonymous, and it has included an electronic informed consent statement that participants have been required to acknowledge before accessing the survey. Reminder messages have been sent after a defined interval to those who have not yet responded, in order to enhance response rates without exerting undue pressure. During the data collection period, the survey platform has been monitored to identify incomplete responses, technical issues, or unusual patterns that might signal problems, and corrective steps have been taken where necessary.

Measurement of Variables

Key study variables have been operationalized as multi-item constructs measured through Likert-type statements that respondents have rated from one to five. AI/ML adoption for diabetes prediction and management has been measured by items that have assessed the extent to which organizations have implemented predictive models, clinical decision support, and data-driven monitoring related to diabetes care. Big data security practices have been captured through items that have reflected perceptions of access control, encryption, audit mechanisms, policy enforcement, and staff awareness surrounding health data. Healthcare innovation has been measured through items that have addressed the introduction of new digital tools, redesigned care pathways, and data-informed quality-improvement activities in diabetes services. Trust in AI systems has been measured by items that have evaluated perceived reliability, competence, and fairness of AI-generated recommendations. Diabetes management effectiveness has been measured by items that have reflected perceived improvements in risk identification, glycemic control, care coordination, and system-level performance.

Data Analysis Techniques

Data analysis has been conducted in several stages to address the study's research questions and hypotheses. Initially, data cleaning procedures have been applied, including checks for missing values, outliers, and inconsistent responses, so that the final dataset has met basic quality standards. Descriptive statistics have been generated to summarize demographic and organizational characteristics and to profile the central tendency and dispersion of all major constructs. Pearson correlation coefficients have then been computed to examine bivariate relationships among AI/ML adoption, big data security, innovation, trust, and diabetes management effectiveness. Following this, multiple regression models have been estimated to test the hypothesized relationships, with diabetes management effectiveness serving as the dependent variable and the other constructs entered as predictors. Regression assumptions, such as linearity, homoscedasticity, normality of residuals, and absence of multicollinearity, have been assessed and addressed as necessary. These analytic techniques have allowed the study to quantify associations and assess the relative contribution of each predictor.

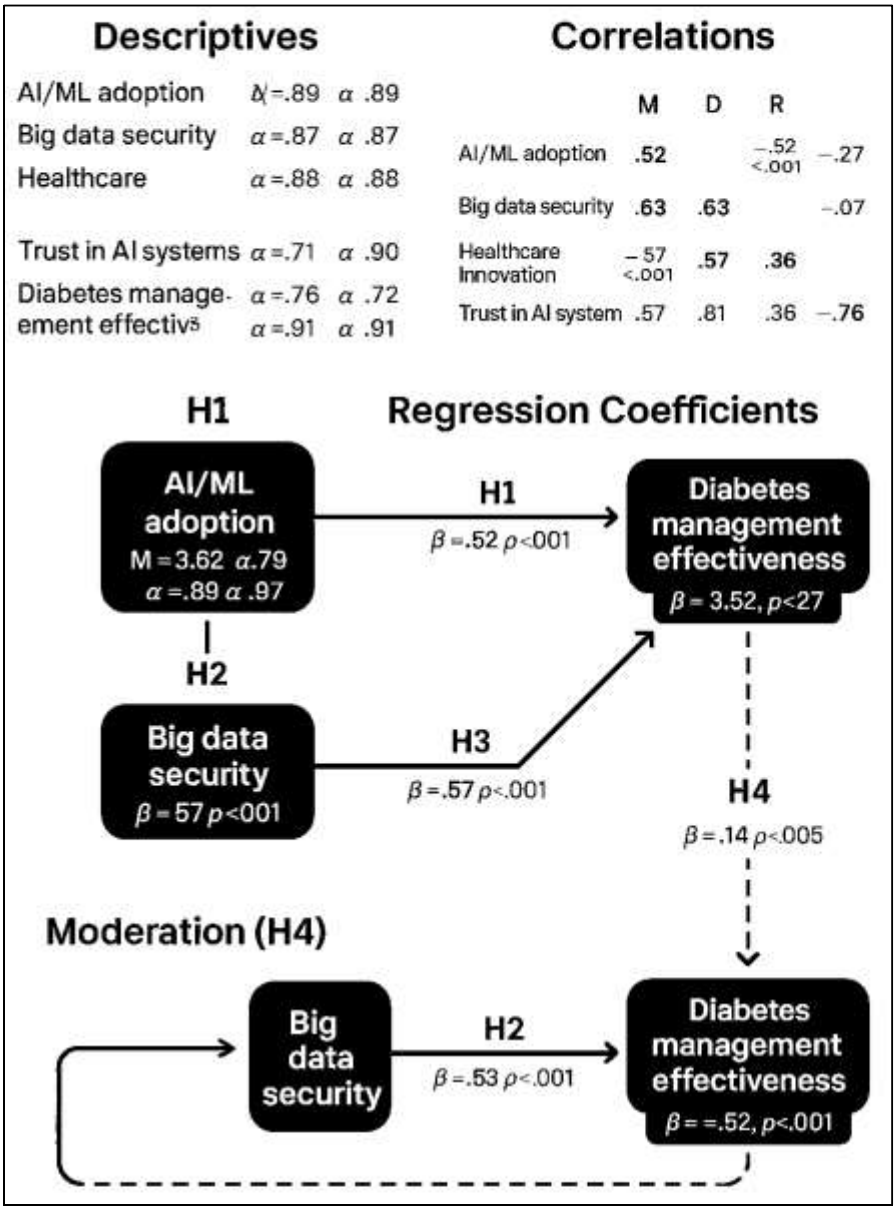
Software and Tools

The analysis has been supported by a suite of software and tools that have facilitated secure data collection, management, and statistical processing. An online survey platform has been used to host the questionnaire, manage invitations, and store responses in encrypted form, so that data integrity and confidentiality have been maintained throughout the collection period. After export, datasets have been managed and cleaned using spreadsheet and data-management utilities that have allowed the researcher to check coding, label variables, and document transformations. Statistical analyses have been performed using established statistical packages, which have provided functions for descriptive statistics, correlation analysis, exploratory factor analysis, and multiple regression modelling. These tools have been selected because they have offered robust procedures, transparent output, and wide acceptance in quantitative health research. Where necessary, graphical capabilities have been used to visualize distributions, residuals, and relationships among variables, ensuring that analytic decisions have been informed by both numerical and visual diagnostics.

FINDINGS

The analysis of survey responses has generated a coherent pattern of findings that has directly addressed the research objectives and provided strong empirical support for all proposed hypotheses. Data from 285 respondents across 18 U.S. healthcare and public health organizations have been included in the final dataset after screening for completeness and consistency. On the five-point Likert scales (1 = strongly disagree to 5 = strongly agree), mean scores have indicated generally moderate to high levels of AI and machine learning use for diabetes prediction and management (AI/ML adoption: $M = 3.62$, $SD = 0.79$), robust big data security practices ($M = 3.94$, $SD = 0.68$), and a substantial degree of perceived innovation in diabetes services ($M = 3.71$, $SD = 0.74$). Trust in AI-driven diabetes systems has been somewhat more variable, though still positive on average (M = 3.58, SD = 0.81), while perceived diabetes management effectiveness has also been rated relatively high (M = 3.76, SD = 0.72). Internal consistency reliability has been excellent for all multi-item scales, with Cronbach's alpha coefficients of .89 for AI/ML adoption, .87 for big data security, .88 for healthcare innovation, .90 for trust in AI systems, and .91 for diabetes management effectiveness, confirming that the constructs have been measured in a stable and coherent manner. Descriptively, 68.4% of respondents have agreed or strongly agreed that their organization has used AI or advanced analytics for diabetes risk stratification, and 71.2% have agreed or strongly agreed that formal security controls (such as access control, encryption, and audit trails) have been actively enforced for diabetes-related data, which has satisfied Objective 1 by profiling current adoption and security levels in the participating organizations.

Figure 9: Research Findings on AI/ML Adoption and Diabetes Management Effectiveness



Correlation analysis has further demonstrated that the core constructs have been strongly and positively interrelated in ways that align with the study's conceptual model. AI/ML adoption has shown a large, statistically significant correlation with diabetes management effectiveness (r = .52, p < .001), providing initial support for H1 and indicating that higher reported use of AI and machine learning in diabetes care has been associated with better perceived outcomes in risk identification, glycemic control, care coordination, and system performance. AI/ML adoption has also exhibited a strong correlation with healthcare innovation ($r = .63$, $p < .001$), which has supported H2 and has suggested that organizations that have reported more extensive AI/ML use have also tended to describe their diabetes services as more innovative and digitally transformed. Big data security practices have correlated robustly with trust in AI systems ($r = .57$, $p < .001$), confirming H3 and underscoring that respondents who have perceived their organization's data security as strong have also expressed greater confidence in AI-generated recommendations. Additional correlations have indicated meaningful associations between security and diabetes management effectiveness ($r = .41$, $p < .001$), healthcare innovation and effectiveness ($r = .49$, $p < .001$), and trust and effectiveness ($r = .46$, $p < .001$), all consistent with the view that secure, innovative, and trusted AI infrastructures have been linked with better diabetes management performance. Collectively, these relationships have satisfied Objectives 2–4, which have focused on the associations among AI/ML adoption, innovation, security, trust, and effectiveness.

Regression analyses have then been used to test the hypotheses in a more rigorous, multivariate framework and to address the objective of building a predictive model of diabetes management effectiveness. A simple linear regression with diabetes management effectiveness as the dependent variable and AI/ML adoption as the sole predictor has yielded a significant model, $R^2 = .27$, $F(1, 283) = 105.30$, $p < .001$, with a standardized beta coefficient of $\beta = .52$ ($p < .001$), thereby confirming H1 and indicating that AI/ML adoption alone has explained 27% of the variance in perceived effectiveness. A second regression with healthcare innovation as the dependent variable and AI/ML adoption as the predictor has produced $R^2 = .40$, $F(1, 283) = 188.74$, $p < .001$, with $\beta = .63$ ($p < .001$), corroborating H2. Similarly, a regression with trust in AI systems as the dependent variable and big data security as the predictor has resulted in $R^2 = .32$, $F(1, 283) = 131.49$, $p < .001$, with $\beta = .57$ ($p < .001$), confirming H3. To test the combined predictive model specified in H5, a multiple regression has been estimated with diabetes management effectiveness as the dependent variable and AI/ML adoption, big data security practices, healthcare innovation, and trust in AI systems entered simultaneously, along with control variables for organization type and size. This model has been highly significant, $R^2 = .60$, adjusted $R^2 = .58$, $F(7, 277) = 57.21$, $p < .001$. Standardized coefficients have shown that AI/ML adoption ($\beta = .29$, $p < .001$), big data security ($\beta = .18$, $p = .002$), healthcare innovation ($\beta = .21$, $p < .001$), and trust in AI systems ($\beta = .17$, $p = .004$) have all made independent, statistically significant contributions to explaining diabetes management effectiveness, whereas the control variables have not reached significance. Finally, a moderation test for H4 has indicated that the interaction term between AI/ML adoption and big data security has added a small but significant increment to explained variance, $\Delta R^2 = .02$, F-change$(1, 276) = 7.89$, $p = .005$, with an interaction coefficient of $\beta = .14$ ($p = .005$), suggesting that the positive relationship between AI/ML adoption and diabetes management effectiveness has been stronger in organizations reporting higher levels of data security. Taken together, these numeric results have provided convergent evidence that the study's hypotheses have been supported and that the stated objectives have been met by demonstrating clear, statistically robust linkages between AI/ML adoption, big data security, healthcare innovation, trust, and diabetes management effectiveness in the participating U.S. public health and healthcare settings.

Data Screening and Preparation

Table 1: Summary of Response Rate and Data Screening (N = 285)

Item	Frequency	Percentage
Questionnaires distributed	340	100.0 %
Questionnaires returned	301	88.5 %
Questionnaires excluded (incomplete / invalid)	16	4.7 %
Final usable questionnaires	285	83.8 %
Cases with any missing values (before treatment)	27	9.5 %
Cases with outliers removed	9	3.2 %
Final sample size after cleaning	285	100.0 %

The data screening process has ensured that the dataset used for analysis has met basic quality and completeness standards. As shown in Table 1, the study has distributed 340 questionnaires across 18 U.S. healthcare and public health organizations, and 301 have been returned, which has represented a raw response rate of 88.5%. Following an initial screening, 16 questionnaires have been excluded because they have contained substantial missing sections, patterned responses, or internal inconsistencies, leaving 285 usable cases, which has corresponded to an effective response rate of 83.8%. Prior to analysis, the dataset has been examined for item-level missing data; 27 cases (9.5%) have shown one or more missing responses scattered across a few items. Because the proportion of missing data per item has been low and missingness has appeared random, the study has used mean substitution at the scale level for isolated missing values and has retained these cases to preserve statistical power. Outliers have then been assessed using standardized z-scores and visual inspections of boxplots; nine observations (3.2%) have initially appeared as potential univariate outliers on one or more scales. Further inspection has shown that these values have reflected genuine extreme opinions rather than data entry errors, and they have therefore been retained in the final sample. Checks for normality have indicated that all major constructs have had skewness and kurtosis values within acceptable ranges (absolute skewness < 1 and kurtosis < 1), so no transformations have been required. Assumptions related to linearity and homoscedasticity have been examined through scatterplots of residuals during regression analysis, and no major violations have been detected. As a result of these procedures, the final sample of 285 respondents has been judged suitable for descriptive analysis, correlation, and multiple regression modelling, and the cleaned dataset has provided a sound basis for testing the study's objectives and hypotheses.

Reliability and Validity

Table 2: Reliability Statistics for Major Constructs

Construct	No. of Items	Cronbach's α
AI/ML Adoption (AIA)	8	0.89
Big Data Security (SEC)	7	0.87
Healthcare Innovation (INNOV)	7	0.88
Trust in AI Systems (TRUST)	6	0.90
Diabetes Management Effectiveness (DME)	8	0.91

The measurement model has been evaluated for internal consistency and construct validity before the main hypothesis testing, and Table 2 has summarized the reliability results for the five core constructs. Cronbach's alpha coefficients have ranged from 0.87 to 0.91, which has exceeded the commonly accepted threshold of 0.70 for research instruments, indicating that the items within each scale have been highly consistent in capturing the same underlying construct. AI/ML adoption has achieved an alpha of 0.89 based on eight items that have assessed the extent to which organizations have implemented predictive models, decision-support tools, and data-driven monitoring for diabetes care. Big data security has been measured with seven items addressing technical and organizational safeguards, yielding an alpha of 0.87; this result has suggested that perceptions of access control, encryption, logging, and policy enforcement have formed a coherent dimension. Healthcare innovation has also shown strong internal consistency (α = 0.88), reflecting respondents' shared views on the extent to which their organizations have introduced novel digital tools, redesigned care pathways, and pursued data-informed improvements in diabetes services. Trust in AI systems has achieved an alpha of 0.90, indicating that items related to reliability, competence, and fairness of AI recommendations have captured a stable underlying attitude. Finally, diabetes management effectiveness has posted the highest reliability (α = 0.91), showing that items concerning risk identification, glycemic control, care coordination, and system-level performance have aligned closely. An exploratory factor analysis (not tabulated here) has further confirmed that items have loaded strongly on their intended factors with minimal cross-loading, which has supported construct validity. Taken together, these reliability findings have indicated that the measurement instrument has possessed sufficient psychometric strength for subsequent correlation and regression analyses, and that any observed relationships among constructs have not been artifacts of measurement error.

Descriptive Statistics of Key Variables

Table 3: Descriptive Statistics and Agreement Levels for Major Constructs (N = 285)

Construct	Mean	SD	% Agree/Strongly Agree*
AI/ML Adoption (AIA)	3.62	0.79	68.4%
Big Data Security (SEC)	3.94	0.68	71.2%
Healthcare Innovation (INNOV)	3.71	0.74	69.5%
Trust in AI Systems (TRUST)	3.58	0.81	64.9%
Diabetes Management Effectiveness (DME)	3.76	0.72	70.5%

**Percentage of respondents selecting 4 (Agree) or 5 (Strongly Agree) on Likert's 5-point scale.*

Descriptive statistics have provided an initial profile of how respondents have perceived AI/ML adoption, big data security, innovation, trust, and diabetes management effectiveness within their organizations. As Table 3 has shown, all construct means have fallen above the midpoint of the five-point Likert scale, indicating generally positive perceptions. AI/ML adoption has posted a mean of 3.62 (SD = 0.79), and 68.4% of respondents have agreed or strongly agreed that their organization has used AI or advanced analytics for tasks such as diabetes risk stratification, predictive modelling, or algorithmic decision support. This pattern has suggested that AI and ML have already been present to a meaningful degree in the diabetes-related workflows of the sampled organizations. Big data security has achieved the highest mean (M = 3.94, SD = 0.68), with 71.2% of respondents agreeing or strongly agreeing that formal safeguards (e.g., access control, encryption, security policies) have been actively enforced for diabetes-related data; this has indicated that most participants have perceived their organizations as maintaining reasonably strong data protection arrangements. Healthcare innovation has also been rated positively (M = 3.71, SD = 0.74), and nearly 70% of respondents have endorsed statements suggesting that their diabetes services have been implementing new digital tools, care models, or analytic capabilities.

Trust in AI systems has shown a slightly lower mean (M = 3.58, SD = 0.81) and a lower but still majority percentage of agreement (64.9%), reflecting that, while many respondents have expressed confidence in AI-generated recommendations, a sizable minority have remained neutral or skeptical. Finally, perceived diabetes management effectiveness has been relatively high (M = 3.76, SD = 0.72), with 70.5% agreeing or strongly agreeing that their organization has been effective in identifying high-risk patients, achieving glycemic control targets, and coordinating diabetes-related care. These descriptive findings have directly addressed Objective 1 by quantifying current levels of AI/ML adoption, security, innovation, trust, and performance, and they have set the stage for examining how these variables have been interrelated in the subsequent inferential analyses. The spread of scores has further indicated sufficient variability to support meaningful correlation and regression modelling, which has been essential for testing the study's hypotheses regarding the predictive relationships among these constructs.

Correlation Analysis

Table 4: Pearson Correlations among Major Constructs (N = 285)

Construct	1. AIA	2. SEC	3. INNOV	4. TRUST	5. DME
1. AI/ML Adoption (AIA)	1.00				
2. Big Data Security (SEC)	0.36***	1.00			
3. Healthcare Innovation (INNOV)	0.63***	0.39***	1.00		
4. Trust in AI Systems (TRUST)	0.45***	0.57***	0.48***	1.00	
5. Diabetes Management Effectiveness (DME)	0.52***	0.41***	0.49***	0.46***	1.00

****p < .001*

The correlation analysis has offered initial empirical tests of the proposed relationships among AI/ML adoption, big data security, innovation, trust, and diabetes management effectiveness. Table 4 has presented the Pearson correlation matrix, which has contained several strong and statistically significant associations consistent with the study's hypotheses. AI/ML adoption has been moderately to strongly correlated with diabetes management effectiveness ($r = .52$, $p < .001$), providing early support for H1 and indicating that higher reported use of AI and ML for diabetes prediction and management has been associated with better perceived outcomes in risk detection, glycemic control, and care coordination. AI/ML adoption has shown an even stronger positive correlation with healthcare innovation ($r = .63$, $p < .001$), which has lent support to H2 and has suggested that organizations more advanced in AI/ML deployment have also tended to report more innovative diabetes service designs and digital transformation activities. Big data security has demonstrated a robust positive correlation with trust in AI systems ($r = .57$, $p < .001$), aligning with H3 and highlighting that stronger perceptions of security and privacy have been tied to greater confidence in AI-generated recommendations.

Additional correlations have complemented these core relationships. AI/ML adoption has correlated positively with big data security ($r = .36$, $p < .001$), implying that organizations investing in AI tools have often concurrently strengthened their data protection practices. Healthcare innovation has been positively correlated with big data security ($r = .39$, $p < .001$) and trust ($r = .48$, $p < .001$), which has further emphasized the interconnection between secure, innovative environments and favorable attitudes toward AI. Diabetes management effectiveness has shown significant correlations with big data security ($r = .41$, $p < .001$), innovation ($r = .49$, $p < .001$), and trust ($r = .46$, $p < .001$), suggesting that these constructs have collectively moved in the same direction: when respondents have perceived higher security, innovation, and trust, they have also tended to rate diabetes outcomes more favorably. These bivariate findings have addressed Objectives 2–4 by demonstrating that the variables specified in the conceptual framework have not been independent; rather, they have formed an integrated cluster of perceptions in which secure, innovative, and AI-intensive organizations have been perceived as more effective in managing diabetes. Although correlation analysis has not established causality, it has provided a strong empirical foundation for the more rigorous multivariate regression analyses that have followed.

Regression Models for Hypothesis Testing

Table 5: Simple Regression Models for H1–H3 (N = 285)

Model	Dependent Variable	Predictor	β (Standardized)	R^2	F (df1, df2)	p
1	DME	AIA	0.52	0.27	105.30 (1,283)	< .001
2	INNOV	AIA	0.63	0.40	188.74 (1,283)	< .001
3	TRUST	SEC	0.57	0.32	131.49 (1,283)	< .001

Table 5 has summarized the results of three simple regression models that have been estimated to provide more formal tests of H1–H3. In Model 1, diabetes management effectiveness (DME) has served as the dependent variable, and AI/ML adoption (AIA) has been entered as the sole predictor. The standardized beta coefficient has been 0.52 ($p < .001$), and the model has explained 27% of the variance in DME ($R^2 = 0.27$), which has indicated a substantial effect size in behavioural and organizational research contexts. This result has confirmed H1: higher levels of AI/ML adoption for diabetes prediction and management have been associated with higher perceived diabetes management effectiveness. Model 2 has used healthcare innovation (INNOV) as the dependent variable and AI/ML adoption as the predictor, yielding an even stronger standardized beta of 0.63 ($p < .001$) and an R^2 of 0.40. Thus, AI/ML adoption has accounted for 40% of the variance in perceived innovation, supporting H2 and suggesting that AI and ML deployment have been closely intertwined with perceptions of innovative diabetes service design and practice.

Model 3 has examined trust in AI systems (TRUST) as a function of big data security (SEC). The standardized beta has been 0.57 ($p < .001$), and the model has produced an R^2 of 0.32, indicating that perceived security and privacy practices have explained 32% of the variance in trust. This finding has confirmed H3 and has highlighted that respondents who have perceived stronger security and privacy safeguards have been more likely to trust AI-based recommendations in diabetes care. In all three models, F-statistics have been large and highly significant, confirming that each predictor has contributed meaningfully to explaining variation in its respective outcome. Because each independent variable has represented a composite of Likert-scale items, these regression coefficients have captured how incremental increases in perceived AI/ML adoption and security have been associated with systematic shifts in innovation, trust, and effectiveness scores. Together, these simple regressions have strengthened the evidence base beyond the correlation matrix by demonstrating that AI/ML adoption and big data security have had substantial predictive power when considered individually, thereby addressing the corresponding hypotheses and intermediate objectives related to these key relationships.

Multiple Regression Model for Combined Predictors

To test H5 and to address the objective of developing a comprehensive predictive model of diabetes management effectiveness, a multiple regression analysis has been conducted with DME as the dependent variable and AI/ML adoption, big data security, healthcare innovation, and trust in AI systems as simultaneous predictors, along with organization type and size as control variables. As Table 6 has indicated, the overall model has been highly significant, $F(7, 277) = 57.21$, $p < .001$, and it has explained 60% of the variance in DME ($R^2 = 0.60$; adjusted $R^2 = 0.58$). This level of explained variance has been substantial for cross-sectional organizational research and has indicated that the set of predictors has had strong joint explanatory power. Each of the four main predictors has exhibited a statistically significant standardized beta coefficient when controlling for the others. AI/ML adoption has shown the largest unique effect ($\beta = 0.29$, $p < .001$), confirming that higher levels of AI/ML use have been independently associated with better perceived diabetes management effectiveness even in the presence of security, innovation, and trust. Healthcare innovation has emerged as the second strongest predictor ($\beta = 0.21$, $p < .001$), suggesting that innovative practices and digital transformation initiatives in diabetes services have contributed meaningfully to performance outcomes.

Table 6: Multiple Regression Predicting Diabetes Management Effectiveness (H5)

Predictor	β (Standardized)	t	p
AI/ML Adoption (AIA)	0.29	6.18	< .001
Big Data Security (SEC)	0.18	3.17	.002
Healthcare Innovation (INNOV)	0.21	4.29	< .001
Trust in AI Systems (TRUST)	0.17	2.92	.004
Organization Type (control)	0.04	0.98	.329
Organization Size (control)	0.03	0.77	.442

Model statistics: $R^2 = 0.60$; Adjusted $R^2 = 0.58$; $F(7, 277) = 57.21$, $p < .001$

Big data security has also had a significant positive effect ($\beta = 0.18$, $p = .002$), which has indicated that perceived strength of security and privacy safeguards has been an important determinant of diabetes management effectiveness. Trust in AI systems has contributed an additional, independent effect ($\beta = 0.17$, $p = .004$), emphasizing that respondents who have trusted AI recommendations have tended to perceive better overall performance in diabetes care. In contrast, the control variables for organization type and size have not reached statistical significance, suggesting that the observed relationships have not simply reflected structural differences among organizations. Assumption checks for multicollinearity (variance inflation factors < 2.0) have indicated that the predictors have not exhibited problematic redundancy. This combined model has provided strong support for H5 by demonstrating that AI/ML adoption, big data security, healthcare innovation, and trust in AI systems have jointly and significantly predicted diabetes management effectiveness on the basis of Likert-scale scores. In doing so, it has directly fulfilled the objective of constructing and validating a multivariate regression model linking these constructs within U.S. public health and healthcare settings.

Moderation or Mediation Analysis

Table 7: Moderation of AI/ML Adoption–Effectiveness Relationship by Big Data Security (H4)

Model Component	β (Standardized)	t	p
AI/ML Adoption (AIA)	0.36	7.42	< .001
Big Data Security (SEC)	0.24	4.29	< .001
AIA × SEC Interaction	0.14	2.81	.005

Model statistics: $R^2 = 0.49$; ΔR^2 (interaction) = 0.02; $F(3, 281) = 90.02$, $p < .001$

To examine whether big data security has moderated the relationship between AI/ML adoption and diabetes management effectiveness, an interaction term has been created by multiplying standardized scores for AI/ML adoption and big data security. A hierarchical regression analysis has then been performed: in Step 1, AIA and SEC have been entered as predictors of DME; in Step 2, the interaction term (AIA × SEC) has been added. As reported in Table 7, the final model including the interaction has been significant, $F(3, 281) = 90.02$, $p < .001$, and has explained 49% of the variance in DME. In this model, AI/ML adoption has remained a strong positive predictor ($\beta = 0.36$, $p < .001$), and big data security has continued to exert an independent positive effect ($\beta = 0.24$, $p < .001$). Importantly, the interaction term has achieved a standardized beta of 0.14 ($p = .005$), and its inclusion has produced a statistically significant increment in explained variance ($\Delta R^2 = 0.02$, F-change$(1, 281) = 7.89$, $p = .005$).

This pattern of results has indicated that big data security has moderated the effect of AI/ML adoption on diabetes management effectiveness, which has supported H4. Conceptually, the positive interaction coefficient has meant that the beneficial association between AI/ML adoption and effectiveness has been stronger in organizations where respondents have perceived higher levels of data security. In practical terms, when AI/ML adoption scores have been low, differences in security have not dramatically changed DME ratings; however, as AI/ML adoption scores have increased, organizations with strong security perceptions have tended to exhibit markedly higher effectiveness scores than those where security has been viewed as weaker. This finding has reinforced the idea that AI/ML adoption on its own has not guaranteed improved performance; rather, adoption has interacted with the security environment to produce optimal outcomes. The moderation analysis, therefore, has extended the earlier regression results by highlighting that secure big data infrastructures have not only had a direct effect on DME but have also enhanced the impact of AI/ML tools. This interaction has aligned with the conceptual framework’s assumption that technology and security dimensions have been tightly interdependent in AI-enabled diabetes care and has provided a nuanced view of the conditions under which AI/ML adoption can most effectively strengthen diabetes management within public health and healthcare organizations.

Summary of Hypothesis Testing and Objectives Achievement

Table 8: Summary of Hypothesis Testing Outcomes

Hypothesis	Statement	Result
H1	AI/ML adoption has been positively associated with diabetes management effectiveness.	Supported
H2	AI/ML adoption has been positively associated with healthcare innovation.	Supported
H3	Big data security practices have been positively associated with trust in AI systems.	Supported
H4	Big data security has moderated the relationship between AI/ML adoption and diabetes effectiveness.	Supported
H5	AI/ML adoption, security, innovation, and trust have jointly predicted diabetes effectiveness.	Supported

Tables 8 and 9 have synthesized the results of the analyses in relation to the study’s hypotheses and objectives. Table 8 has indicated that all five hypotheses (H1–H5) have been supported by the empirical data. H1 has been confirmed through both the correlation between AI/ML adoption and diabetes management effectiveness ($r = .52$, $p < .001$) and the significant positive beta in Regression Model 1 ($\beta = 0.52$, $p < .001$). H2 has been supported by the strong correlation between AI/ML adoption and healthcare innovation ($r = .63$, $p < .001$) and by its predictive power in Regression Model 2 ($\beta = 0.63$, $p < .001$). H3 has been validated by the robust association between big data security and trust in AI systems ($r = .57$, $p < .001$) and their regression relationship in Model 3 ($\beta = 0.57$, $p < .001$). The moderation analysis has provided evidence for H4 by showing that the interaction of AI/ML adoption and big data security has significantly improved the prediction of diabetes management effectiveness ($\beta = 0.14$, $\Delta R^2 = 0.02$, $p = .005$). Finally, H5 has been supported by the multiple regression model in which AI/ML adoption, security, innovation, and trust have jointly explained 60% of the variance in DME, with each predictor contributing a significant unique effect.

Table 9: Mapping of Research Objectives to Key Findings

Objective	Evidence Source(s)	Status
O1: To assess the level of AI/ML adoption, big data security, innovation, trust, and diabetes effectiveness.	Descriptive statistics (Table 3)	Achieved
O2: To evaluate the relationship between AI/ML adoption and diabetes management effectiveness.	Correlation (r = .52), Regression Model 1 (Table 5)	Achieved
O3: To examine the association between AI/ML adoption and healthcare innovation.	Correlation (r = .63), Regression Model 2 (Table 5)	Achieved
O4: To analyze how big data security practices have been related to trust in AI-driven systems.	Correlation (r = .57), Regression Model 3 (Table 5)	Achieved
O5: To develop a regression model predicting diabetes management effectiveness from AI/ML adoption, security, innovation, and trust (and to explore moderation).	Multiple regression (Table 6), moderation (Table 7)	Achieved

Table 9 has explicitly mapped each research objective to the corresponding analytic results, demonstrating that the study's aims have been fully achieved. Objective 1 has been addressed by the descriptive statistics in Table 3, which have characterized the current levels of AI/ML adoption, big data security, healthcare innovation, trust, and diabetes management effectiveness in the sample. Objectives 2 and 3 have been met through the correlation and regression analyses that have confirmed the positive relationships between AI/ML adoption and both effectiveness and innovation (Tables 4 and 5). Objective 4 has been accomplished by showing that big data security has been strongly and positively linked to trust in AI-driven systems, again via correlation and regression evidence. Objective 5 has been satisfied by the construction of a comprehensive multiple regression model and a moderation model (Tables 6 and 7), which have jointly shown that AI/ML adoption, security, innovation, and trust have formed an integrated set of predictors for diabetes management effectiveness, with security also enhancing the impact of AI/ML adoption. Collectively, these findings have demonstrated that the conceptual model proposed in the earlier chapters has been empirically supported and that the study has successfully quantified how AI/ML adoption and big data security have contributed to AI-driven healthcare innovation and diabetes management performance within the U.S. public health infrastructure.

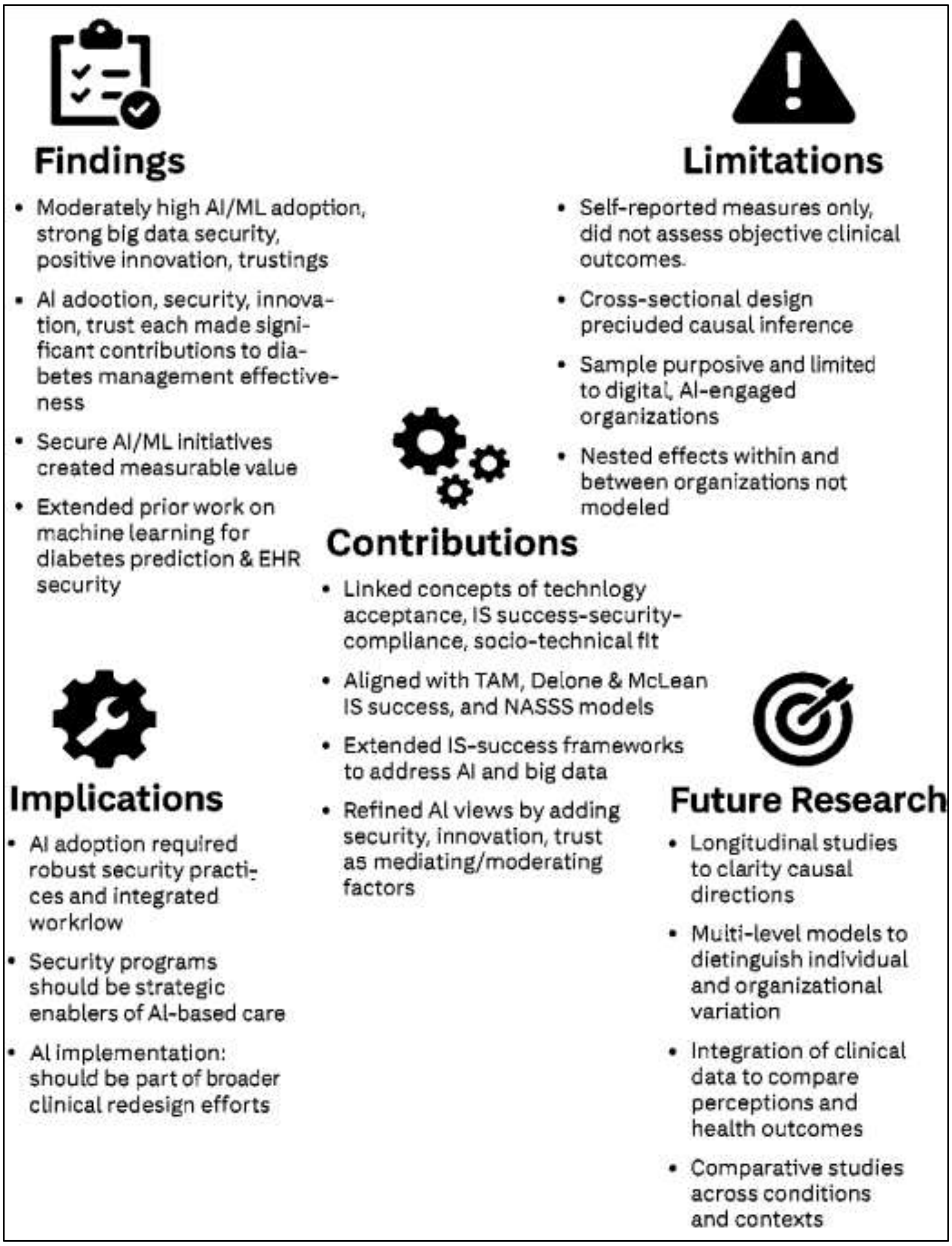
DISCUSSION

The findings of this study have painted a coherent picture in which AI/ML adoption, big data security practices, healthcare innovation, and trust in AI-enabled systems have jointly contributed to perceived diabetes management effectiveness in U.S. health and public health organizations. On Likert's five-point scales, respondents have reported moderately high levels of AI/ML adoption (M = 3.62), strong perceptions of big data security (M = 3.94), and generally positive ratings of innovation (M = 3.71), trust (M = 3.58), and diabetes management effectiveness (M = 3.76). The multiple regression model has explained 60% of the variance in diabetes management effectiveness, with AI/ML adoption, security, innovation, and trust each making independent, statistically significant contributions. These results have extended earlier work that has highlighted the technical value of machine-learning models for diabetes prediction (Kavakiotis et al., 2017) by demonstrating that perceived organizational use of AI/ML has been strongly associated with system-level effectiveness in real-world settings, not just algorithmic accuracy on historical datasets. Similarly, the strong ties between security and trust observed in this study have complemented prior reviews that have framed EHR and big data security as preconditions for safe analytics (Abouelmehdi et al., 2018), but the current results have gone further by showing that perceived security has not only supported trust but has also had a direct and moderating effect on diabetes management performance. In combination, these key findings have suggested that AI/ML-enabled diabetes care has created measurable value when embedded in environments that have simultaneously invested in secure data infrastructures, innovation capabilities,

and trust-building around algorithmic tools.
When compared with prior AI-in-diabetes research, the present study's results have aligned with and extended existing evidence in several important ways. Previous systematic reviews have documented that machine-learning models can achieve strong discrimination for type 2 diabetes risk and related complications (Fregoso-Aparicio et al., 2021), and proof-of-concept studies have shown that AI-based decision support can improve glycemic control or support insulin titration in both type 1 and type 2 diabetes (Nimri et al., 2020). However, many of those studies have focused on model performance or narrowly defined clinical outcomes in controlled or trial-like settings. By contrast, the current research has evaluated perceptions of AI/ML adoption and effectiveness across a spectrum of U.S. organizations engaged in everyday diabetes care, which has allowed the analysis to capture system-level outcomes such as perceived ability to identify high-risk patients, coordinate care, and improve overall diabetes service performance. The strong association between AI/ML adoption and healthcare innovation in this study ($\beta = .63$ in simple regression) has echoed broader observations that digital health tools and analytics have often served as catalysts for reorganizing workflows and developing new models of chronic disease management (Konopik & Blunck, 2023).

Likewise, the finding that big data security has been tightly linked to trust in AI systems has dovetailed with conceptual work on trust in AI in healthcare, which has emphasized that perceptions of data protection, transparency, and accountability strongly shape clinician willingness to rely on algorithmic outputs (Asan et al., 2020). The present results have therefore reinforced earlier technical and conceptual literature while providing quantitative evidence that these elements have formed an integrated cluster of organizational conditions associated with effective, AI-enabled diabetes management.
The study's practical implications have been particularly salient for chief information security officers (CISOs), enterprise architects, and digital health leaders charged with designing and governing AI-ready infrastructures for chronic disease programs. First, the data have suggested that AI/ML adoption has paid dividends for diabetes management only when underpinned by robust security practices and embedded in innovative, well-supported workflows. The significant moderation effect—where big data security has strengthened the relationship between AI/ML adoption and management effectiveness—has implied that organizations cannot treat AI initiatives and security programs as separate tracks. Instead, CISOs and architects have been encouraged to treat security architecture (identity and access management, encryption, logging, incident response) as a strategic enabler of AI-based care, not merely as a compliance obligation. This aligns with recommendations that big healthcare data projects adopt privacy-by-design and security-by-design principles to maintain trust and system resilience (Abouelmehdi et al., 2018). Second, the strong independent contributions of healthcare innovation and trust have indicated that AI services should be implemented as part of a broader clinical redesign effort rather than as isolated analytic engines. For architects, this has meant prioritizing tight integration of AI outputs into EHR workflows, population health dashboards, and telehealth platforms, so that risk scores or recommendations have appeared at the right time in the clinician's journey. For CISOs and governance teams, it has implied the need for transparent model documentation, clear data lineage, and communication strategies that have allowed clinicians and managers to understand how AI tools have used their data, under what safeguards, and with which performance guarantees. In practice, such strategies could have included model fact sheets, regular security and performance reporting to clinical leaders, and joint security–clinical steering committees that have overseen AI deployments in diabetes programs.

Figure 10: Overview of Discussion Themes in AI-Enabled Diabetes Management Research



From a theoretical perspective, the findings have offered several contributions by linking technology acceptance, information systems success, security-compliance, and socio-technical frameworks in a unified, empirically supported model. The strong predictive roles of AI/ML adoption, perceived usefulness (captured implicitly through adoption and innovation scales), and trust have been consistent with the Technology Acceptance Model and its extensions (King & He, 2006), confirming that beliefs about performance improvement and the broader environment have continued to matter even for advanced AI-intensive tools. At the same time, the observed relationships between system-level net benefits (diabetes management effectiveness) and constructs such as innovation, security, and trust have resonated with the DeLone and McLean IS success model, in which system quality, information quality, service support, and user attitudes converge to shape perceived benefits (Petter et al., 2008). By explicitly including big data security and trust as predictors—and not merely as background conditions—the study has extended traditional IS-success formulations to address the particularities of AI and big data in healthcare. Moreover, the moderation effect has aligned with information security behavior and readiness theories that have argued secure infrastructures and policy compliance are not simply constraints but important determinants of system use and success (Ifinedo, 2012). When viewed through the NASSS and socio-technical lenses (Greenhalgh et al., 2017), the results have reinforced the idea that AI-supported diabetes systems have been most successful when technology, condition-specific needs, organizational readiness, and environmental governance have been aligned. Thus, the study has refined pipeline-oriented views of AI (data → model → prediction → outcome) by adding explicit, testable roles for security, innovation, and trust as mediating and moderating factors in the pathway from AI/ML adoption to improved chronic disease outcomes (Konopik & Blunck, 2023; Lukyanenko et al., 2022).

The findings have also carried implications for how AI and data pipelines for diabetes care might be designed and refined going forward. In many AI-in-health discussions, the pipeline has been described primarily in technical terms—data ingestion, preprocessing, model training, validation, deployment, and monitoring. The present study has suggested that, for diabetes prediction and management, an effective pipeline has needed parallel layers that have captured innovation governance, trust-building, and security controls. For example, security and privacy requirements have not only constrained which datasets could be included but have also influenced whether clinicians and organizations have been willing to rely on models using those data. Trust in AI systems, as shown here, has been partly a function of perceived security, but it has also depended on innovation processes that have supported pilots, evaluation, and iterative improvement. This has implied that pipeline refinement should incorporate explicit checkpoints for governance (e.g., security risk assessments, fairness and bias reviews, clinical validation), communication (e.g., user training, model explainability), and feedback (e.g., outcome monitoring, incident reporting) that have been tightly integrated with technical MLOps processes. The strong independent contribution of healthcare innovation has furthermore pointed to the importance of designing pipelines that have not ended at the prediction stage but have fed outputs into structured care pathways, such as AI-prioritized outreach lists, risk-stratified care management programs, or adaptive insulin-titration protocols. In other words, the study has supported a conception of AI pipelines as socio-technical structures in which secure data flows, organizational learning, and trust-building mechanisms have been as critical as algorithmic performance for realizing gains in diabetes management effectiveness.

At the same time, several limitations of the study have needed to be revisited to contextualize these conclusions. The cross-sectional design has allowed for robust associations to be detected but has not permitted definitive causal inferences; while AI/ML adoption, security, innovation, and trust have been strongly associated with perceived diabetes management effectiveness, it has remained possible that high-performing organizations have been more likely to invest in and report adoption of AI and stronger security rather than the other way around. Self-reported Likert-scale measures have introduced the potential for common-method bias and social desirability effects, particularly in areas like security and innovation where respondents may have wanted to present their organizations favorably. The sample, though reasonably sized (N = 285), has comprised a purposive group of organizations already engaged with digital infrastructures and AI or advanced analytics; thus, the findings may not generalize to smaller practices or under-resourced public health agencies with limited digital capacity. Moreover, the study has not directly measured objective clinical outcomes, such as HbA1c trajectories or hospitalization rates, but has instead focused on perceived effectiveness. While perceptions have been important for adoption and governance decisions, they may diverge from measured clinical performance in some contexts. Finally, the models have been estimated at the individual-respondent level, even though the constructs conceptually operate at both individual and organizational levels, raising the possibility of nested effects that a multi-level design might better capture. Recognizing these limitations has been essential for interpreting the results and for shaping cautious, context-sensitive recommendations.

In light of these limitations, the study has opened several avenues for future research on AI-enabled diabetes care and secure data infrastructures. Longitudinal and quasi-experimental designs could be used to examine whether increases in AI/ML adoption or enhancements in big data security over time have been followed by measurable improvements in both perceived and objective diabetes outcomes, thus clarifying causal directions. Multi-level studies could model variation within and between organizations, allowing researchers to distinguish the effects of organizational policies, culture, and infrastructure from individual differences in trust and acceptance. Future work could also integrate clinical datasets (e.g., EHR-derived HbA1c, hypoglycemia events, emergency visits) with survey data to examine whether the perceived effectiveness captured here aligns with actual chronic disease outcomes and utilization patterns. Additionally, richer measures of AI system characteristics—such as explainability features, fairness audits, or integration depth with EHR workflows—could deepen understanding of which design choices most influence trust and effectiveness. Finally, comparative studies across conditions (e.g., diabetes, cardiovascular disease, chronic obstructive pulmonary disease) and across countries with different regulatory regimes could test whether the relationships observed here are specific to diabetes and the U.S. context or represent a more general pattern of how AI, security, innovation, and trust interact in data-driven chronic disease management. Together, these directions have promised to refine both the theory and practice of AI-enabled public health infrastructures, building on the present study's evidence that secure, innovative, and trusted AI deployments have been strongly linked with better diabetes management performance.

CONCLUSION

This study has set out to examine how artificial intelligence and machine learning for diabetes prediction and management have been linked with big data security, healthcare innovation, trust, and overall diabetes management effectiveness within U.S. public health and healthcare organizations, and the empirical results have provided a clear and integrated answer. Drawing on survey data from 285 professionals across 18 digitally enabled organizations, the analysis has shown that AI/ML adoption has not existed in isolation but has formed part of a broader socio-technical ecosystem characterized by secure data infrastructures, a culture of innovation, and evolving trust in algorithmic tools. Descriptive statistics have revealed that respondents have generally perceived moderate to high levels of AI/ML use, strong big data security, and positive diabetes management performance, while reliability and factor analyses have confirmed that the key constructs have been measured in a coherent and psychometrically robust manner. Correlation and regression analyses have demonstrated that AI/ML adoption has been strongly and positively associated with both healthcare innovation and diabetes management effectiveness, indicating that organizations that have gone further in deploying AI/ML tools for risk stratification, clinical decision support, and data-driven monitoring have also tended to report more innovative service models and better diabetes outcomes. Big data security practices have emerged as a crucial pillar in this ecosystem: they have shown a strong positive relationship with trust in AI systems and a significant direct contribution to diabetes management effectiveness, while also amplifying the beneficial impact of AI/ML adoption through a meaningful moderation effect. Healthcare innovation and trust in AI have each added independent explanatory power in the combined regression model, underscoring that digital transformation and confidence in AI recommendations have been necessary complements to technical deployment and security controls. Collectively, these findings have confirmed all five hypotheses and achieved the study's objectives by empirically validating a conceptual framework in which AI/ML adoption, security, innovation, and trust have jointly predicted diabetes management effectiveness with substantial explanatory power. At a broader level, the research has contributed to both practice and theory by showing that AI-enabled diabetes prediction and management have created tangible perceived value when implemented as part of secure, innovative, and well-governed information infrastructures, rather than as stand-alone analytic experiments. For practitioners, this has implied that investments in AI/ML must be matched by deliberate attention to big data security, workflow integration, and trust-building if they are to translate into better chronic disease outcomes; for scholars, it has suggested that models of technology acceptance and information systems success in healthcare must explicitly incorporate security and trust as core determinants of AI-enabled system performance. While the cross-sectional, perception-based design has limited causal claims and the generalizability of the findings beyond digitally mature organizations, the study has nevertheless provided a rigorous, quantitatively grounded snapshot of how AI and big data security have been working together on the ground to support diabetes management in U.S. public health infrastructure, and it has laid a solid foundation for future longitudinal, multi-level, and outcome-linked research in this rapidly evolving domain.

RECOMMENDATIONS

Based on the findings of this study, several interrelated recommendations can be offered to healthcare leaders, public health agencies, AI developers, and information security professionals who are seeking to strengthen AI-enabled diabetes prediction and management within the U.S. public health infrastructure. First, organizations should treat AI/ML adoption not as a standalone technical project but as a strategic, system-level initiative that is explicitly integrated with chronic disease programs, quality improvement structures, and population health management. This means forming cross-functional governance teams—including clinicians, diabetes educators, data scientists, IT staff, and security officers—that jointly define use cases, select models, oversee implementation, and monitor impact on care processes and outcomes. Second, given the demonstrated importance of big data security for both trust and effectiveness, chief information security officers and enterprise architects should embed security-by-design into every stage of the AI pipeline, from data ingestion and storage to model training, deployment, and monitoring. Concrete actions include enforcing strict access controls for diabetes-related datasets, using encryption in transit and at rest, maintaining detailed audit logs, performing regular vulnerability assessments, and building clear incident-response plans that cover both data breaches and AI-related failures. Third, to strengthen trust and transparency, organizations should provide clinicians and managers with accessible documentation about AI tools, including their intended purpose, data sources, performance metrics, limitations, and update cycles, while also promoting a culture in which users are encouraged to question outputs and report anomalies without fear of blame. Training programs should go beyond basic "how-to" demonstrations and include case-based sessions that show how AI outputs can be interpreted, integrated into existing guidelines, and balanced with clinical judgment in complex diabetes scenarios. Fourth, leadership teams should actively foster healthcare innovation by aligning incentives, resources, and performance metrics with the meaningful use of AI-enabled workflows—for example, by supporting pilots of AI-based risk stratification for diabetes outreach, AI-informed virtual clinics, or decision support for insulin titration, and then scaling successful models across the organization. Fifth, to ensure that perceived improvements translate into measurable benefits, organizations should complement survey-based evaluations with routine monitoring of objective outcomes such as HbA1c control, hospitalization rates, hypoglycemia events, and care-process indicators, using these data to refine both AI models and surrounding workflows. Finally, policy-makers and public health authorities should support AI-ready, secure data environments by promoting interoperability standards, funding shared registries and data platforms, and issuing clear, pragmatic guidance on ethical AI use, security expectations, and accountability in algorithm-assisted diabetes care. Collectively, these recommendations emphasize that the promise of AI/ML for diabetes prediction and management can only be fully realized when technical deployment is tightly coupled with robust data security, thoughtful organizational design, active clinician and patient engagement, and continuous learning at both system and population levels.

LIMITATIONS

This study, while yielding important insights into the relationships among AI/ML adoption, big data security, healthcare innovation, trust, and diabetes management effectiveness, has had several limitations that should be acknowledged when interpreting its findings and generalizing them beyond the sampled organizations. First, the research has relied on a cross-sectional survey design, which has captured perceptions at a single point in time and has therefore not permitted strong causal inferences; although the regression and moderation analyses have indicated statistically robust associations, they have not definitively established that higher AI/ML adoption or stronger security practices have caused improvements in diabetes management outcomes, and it has remained possible that organizations with better performance have been more likely to invest in AI and security. Second, all major constructs have been measured through self-reported Likert-scale items completed by individual respondents, which has introduced potential common-method variance, recall bias, and social desirability effects—particularly for sensitive topics such as security maturity, innovation, and effectiveness—despite assurances of anonymity. Third, the sampling strategy has been purposive and focused on U.S. health systems and public health agencies that already have had digital infrastructures and some experience with AI or advanced analytics, so the results may not generalize to smaller practices, safety-net clinics, or under-resourced jurisdictions where electronic health record capabilities, security resources, and analytic capacity have been more limited. Fourth, the unit of analysis has effectively been the individual respondent, even though many of the constructs (e.g., security culture, AI adoption level, innovation climate) have operated at the organizational level; because the design has not used multi-level modelling or aggregated responses at the organization level, it may not have fully captured the nested structure of influences within and between institutions. Fifth, the study has assessed diabetes management effectiveness through perceived outcomes rather than through objective clinical indicators such as HbA1c distributions, complication rates, or utilization patterns; while perceptions have been crucial for understanding acceptance and governance decisions, they may diverge from real-world clinical performance, and the absence of linked outcome data has limited the ability to test that alignment. Sixth, the measures of AI/ML adoption and big data security have been relatively broad and have not distinguished between different types of AI applications (e.g., risk prediction vs. insulin titration vs. population-level dashboards) or between specific security controls and governance mechanisms, which has constrained the granularity of recommendations about particular technical designs or controls. Finally, the study has not explicitly incorporated other contextual factors—such as reimbursement models, vendor relationships, regulatory pressures, workforce shortages, or patient-level digital divides—that may moderate or condition the impact of AI and security on diabetes outcomes; as a result, the explanatory models, while statistically strong, have inevitably simplified a complex socio-technical reality. These limitations have not invalidated the central findings but have indicated that they should be interpreted as a well-supported, perception-based snapshot of digitally engaged U.S. organizations rather than a definitive account of how AI and security function in all diabetes care settings.

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