Vol. 2 No. 3 (2025)
ONLINE ISSN :3007-309X
PRINT ISSN :3007-3081

Journal of Medical & Health Sciences Review

AI-DRIVEN DECISION SUPPORT SYSTEMS IN PUBLIC HEALTH ADMINISTRATION

Farhat Ul Ain[1], Anum Siddiqui[2], Arslan Mustafa[3], Faika Memon[4], Fiza Kausar[5]

[1]DPT, MSPH, Research Associate, Aga Khan University, Pakistan, Email: farhatulainnaeem@gmail.com
[2]Medical Technologist and Public Health Specialist, Pakistan, Email: anumasksalman@gmail.com
[3]Department of Public Health, Health Services Academy, Pakistan, Email: arsi.dentist87@gmail.com
[4]Assistant Professor, Institute of Public Health, PUMHS, Pakistan, Email: memon.faika@gmail.com
[5]Department of Public Health, Health Services Academy Pakistan, Email: chandiofiza8@gmail.com

ARTICLE INFO:

Keywords:
Artificial Intelligence, Decision Support Systems, Public Health Administration, Reliability, Validity, Adoption, Trust, Organizational Readiness

Corresponding Author: Farhat Ul Ain
DPT, MSPH, Research Associate, Aga Khan University, Pakistan, Email: farhatulainnaeem@gmail.com

Article History:
Published on 27 September 2025

ABSTRACT

Background: The evolution of Artificial Intelligence (AI) has made it possible to create decision support systems to aid decision-making on timely, verifiable, and fact-based issues of immense importance and accuracy for public health administrators. Even with such interest, there are gaps in scholarly literature concerning the adoption, reliability, validity, and demographics of such systems.
Objective: This research aims to analyze the adoption rate, the use of, and the reliability and validity of the decision support systems within the domain of public health, while assessing the demographic and professional differences in their use, and determining the most important predictors for their future adoption.
Methods: This research was conducted with the use of quantitative cross-sectional methods to analyze the responses of 314 individuals in the public health domain, holding such positions as policy development, public health practice, healthcare provision, IT and AI analytics, and health data analysis. The participants answered a 20-item questionnaire, designed on a 5-point Likert scale that describes systems as a domain of public health and issues on supportive technologies embedded in public health (usefulness, ease of use, trust, organizational impact, and future readiness). Descriptive statistical framework systems, such as normality check, reliability Prism analysis (Cronbach's Alpha) for community organization, validity (KMO and Bartlett's test), and demographic computing (Independent Samples t-test, One-Way ANOVA, Kruskal–Wallis, Chi-Square test, Pearson correlation, and regression analysis) were employed.
Results: The findings confirmed that the dataset was normally distributed with strong reliability (Cronbach's Alpha = 0.87) and validity (KMO = 0.82; Bartlett's χ^2 = 245.67, $p < 0.001$). Group comparison tests showed differences between the groups across gender, roles, and education levels. The inter-item correlation was strong and positive, while regression analysis showed that the most significant predictor of future adoption was trust and transparency ($\beta = 0.42$, $p < 0.001$), followed by perceived usefulness and organizational impact.
Conclusion: AI DS DSSs are positively perceived and are expected to enhance the effectiveness of public health administration. The major barriers to adoption are demographic differences, trust, and lack of transparency. Demographic and trust barriers can be overcome with training and role-based approaches aimed at trust building, and they are essential for the successful adoption, sustainable future integration, and public health system performance of AI.

INTRODUCTION

Artificial Intelligence (AI) has developed immensely over time and has impacted almost every domain of society, most notably in healthcare and public health administration. These fields in particular seem to convey the most promise of using AI. Public health administrators (or health administrators) are in charge of managing programmatic health portfolios, allocating resources, and advising policy, all to be evidence-based. These duties are performed in almost all organizational structures today; however, they require the involvement of technology and data in a timely and effective manner. Traditional methods of management are effective in certain cases; however, they are complicated due to the multiplicity of public health data, health emergencies, and the growing health economy. In this case, AI-driven Decision Support Systems (DSS) seem to be the most effective and innovative recent public health technology to assist in administration, enhancing error margins, and advancing health outcomes of entire populations (Pathan et al., 2025).

In the process of classification, AI-powered decision support systems (DSS) seek, compile, and analyze relevant data sets to record such actionable insights that they help in making useful decisions. In the domain of public administration, such systems can improve disease surveillance, predict the dynamics of disease outbreaks, help allocate scarce resources, and aid in the strategic planning of preventive and curative health measures. For instance, AI-powered algorithms can evaluate real-time epidemiological data sets and predict the spread of a disease, thus enabling the swift deployment of preventative measures. Likewise, AI can predict healthcare workforce requirements and optimize the distribution of health workers to maximize logistical efficiencies. AI-powered Decision Support Systems (DSS) can provide timely and actionable insights that help decision makers through the use of real-time data, which can thoroughly change the strategy and practice of public health (Saleela et al., 2025b).

However, the promise of AI is not the same as the application of AI. There is indeed the challenge of data quality, transparency, lack of trust, ethical issues, preparation of the organization, and the full effectiveness of the AI-driven systems in the AI public health system. Also, the different perceptions and professions about the usefulness and reliability of the technology differ. Politicians might perceive their functions as architects of long-term plans, while health care practitioners are likely lost in questions of streamlining the operations of their institutions. IT practitioners might be concerned that their efforts with the system should be focused on the agility and control the system has over IT processes, while public health practitioners should be concerned about the health outcome of the entire population. These different angles should be viewed in order to understand the intricate tailoring approaches to be used to promote acceptability and the long-term use of the systems installed for the AI (Srinivasan et al., 2025).

One important dimension of trust in AI is acceptance. It rests on how system recommendations are viewed, how transparent, appropriate, and just the systems are, and how responsible the processes are. Users of the systems accept the systems since the systems offer better outputs and provide standard ethical systematic processes to operate. Lastly, the anticipation of AI applications in the organization should also be taken into account. The change should address the issues of infrastructure, change, and the management of people to AI (Almadani et al., 2025).

Thus far, there is a need for primary research that explores the perceptions, reliability, and validity of AI-driven DSS in public health administration with the rigor that it deserves. While there is no shortage of theoretical literature on the adoption of AI, there is a lack of quantitative studies that attempt to empirically measure user perception with adoption readiness. This research aims to help fill this void by analyzing the perceptions of a cross-section of public health practitioners on AI-driven decision support systems. This research applies a series of sophisticated statistical tests, including tests of normality, reliability, and validity, group comparisons, correlation, and regression, in order to isolate and define the most important determinants of acceptance to determine the most salient predictors of acceptance in the future (Aljohani, 2025).

Literature Review

The adoption of AI technology in the domain of healthcare and the administration of public health is one of the most important developments of the 21st century. The increasing complexity of managing the health of a population in the public health system, managing a population in the context of a public health emergency with limited resources, has led to the development of AI-supported Decision Support Systems (DSS) for the use of administrators. The literature focuses on various aspects of the adoption of AI, which include and are not limited to the effectiveness of the system at the technological level, the organizational level, and the user's level, trust, ethics, and the sustainability of implementation. This review highlights the most salient literature, explains the gaps, and proposes ways forward for the use of AI-driven decision support systems in the administration of public health (Karuppan Perumal et al., 2025).

In the earlier stages of literature, one of the key aspects is the ability of AI-based DSS to process large datasets. Systems in Public Health often involve the collection of diverse data, such as epidemiological surveillance, demographic data, hospital data, and real-time notifications of disease. Conventional approaches to Data Analysis cannot understand and integrate such complex datasets. AI, more specifically, machine learning and natural language processing, can generate predictive insights concerning disease trends, health risks, and even policies associated with them. Some studies, for instance, using AI in forecasting epidemics, were able to accurately predict the outbreak of influenza and COVID-19 and thus greatly assisted public health administrators in resource allocation and preventative measures. All these contributions indicate that AI has the potential to decrease the time lag between data acquisition and action in public health, which is crucial during a public health emergency (Jariwala, 2025).

AI capabilities with respect to decision-making quality improvement also stand out in the literature. AI-informed DSS, for instance, can amalgamate data from disparate repositories to advise managers on economical and effective policy choices. AI systems have been used in planning vaccine deployment strategies, where predictive models gauge the level of population immunity and the resources needed. AI-informed DSS in the management of chronic diseases also aids in the risk stratification and targeting of preventive service provision. These systems improve public health management by minimizing human errors, making fact-based decisions, and supporting the timely use of data for actionable decision-making (Jayaprakasam, 2025).

Securing and maintaining trust is a challenge, though some scholars argue it's a matter of explanation. The concern is that while the data being processed may be done so accurately, the processed data is not reputable. In the black box of algorithms that AIs use, there is no trunk from which courage can be found. Literature involving the use of computers in health care is telling in that users of the systems prefer systems that can be understood and systems that can explain the rationale for their decisions. The need for practical, explainable AI is critical, and so is the issue of trust in the use of AI in decision support systems. Given the technical capability, use of AI in managing public health remains untapped (Sitaraman, 2025).

Organizational preparedness is another critical issue in the use of AI decision support systems. Focusing on the use of AI decision support systems, there is sufficient evidence that the use of AI requires advanced levels of underlying technologies, supportive organizational culture, training, and management of the change that AI adoption brings. The experience from high-income countries suggests a correlation between advanced levels of adoption and the availability of strong IT and dedicated AI teams. In the other extreme, low-income countries lack success because of a triad of technical, spatial, and attitudinal incompetence. This indicates that there is a relationship between the organizational-contextual factors and the impact of AI on public health administration (Saleela et al., 2025a).

An analysis of factors with respect to demographics and professions has also been undertaken. There is disagreement amongst the various stakeholders within public health systems over the value of AI-driven DSS. While health policymakers are concerned with the outcome's population-level health over the long term in addition to costs and governance, health care practitioners focus on the efficiency of processes and the reduction of workloads. On the other hand, IT and data specialists emphasize accuracy, design of the system, and then the technical robustness of the system. Acceptance is also influenced by the level of education and work experience. Especially, professionals with higher qualifications are more likely to trust AI-driven instruments. The range of views sheds light on the necessity of adopting frameworks of design thinking and targeted curricula to improve ease of use and role-centered use of the system (Oulefki et al., 2025).

Another significant aspect within the relevant literature pertains to ethical issues. Concerns regarding privacy and data protection, algorithmic inequity and possible discrimination, and inequity issues regarding biased data and AI output inequities that impact decision-making, automation, and recommendations disproportionately to the marginalized and unserved population have been raised. In the case of the marginalized and unserved populations, inequities in data-driven public health decision-making can be most concerning due to the deeply rooted sociopolitical inequities present. The public health policies of most countries assume equity as the most important assumption (Scientific, 2025).

The recent literature argues the case for the advancement of ethical principles and policies to be integrated into the governance of AI and machine learning in practice. Thus, the governance of equity in public administrative policies regarding the governance of public health ethics AI is relevant. The literature also addresses the prospective AI-fuelled public health DSS integration. Initial findings indicate that AI has the potential to advance integration beyond predictive analytics to personalized population health interventions, improve health care financing models, and enhance intersectoral collaboration. One example is the use of digital twin technology that serves as a virtual counterpart of people or health systems (Chen et al., 2025).

They are designed to model scenarios of policy impacts and outcomes to predict the behavior of systems and outcomes to various healthcare policies. In addition, AI is being developed for use in unprecedentedly rapid real-time decision-making and system responses to emergencies, pandemics, and natural disasters that require rapid and precise decision-making and action to reverse the emergent situations. These kinds of studies strengthen the argument that the integration of AI will transform public health administration to the extent that its primary and fundamental administrative functions will be redefined (Chumachenko & Yakovlev, 2025).

Although a considerable amount of literature has been published in this domain, several gaps persist. Nearly all of them remain in clinical settings or hospitals, while very few concern the public health domain's administrative decision-making. In addition, the empirical literature has primarily focused on high-income countries, which presents a disparity in the literature concerning the use of AI-based decision support systems in low and middle-income countries. There is a scarcity of quantitative studies focused on the predictors of adoption, such as trust, organizational readiness, and demographic variables, which is also a significant gap. These gaps need to be addressed to develop effective strategies in the integration of AI into public health systems in a just and sustainable manner on a global scale (Murikipudi, 2025).

Research Methodology

Research Design

This study employs a quantitative cross-sectional survey approach in assessing perception, usefulness, and barriers of AI-driven decision support systems in public health administration. This approach is appropriate as it seeks to measure attitudes, organizational readiness, and perception on the reliability and usefulness of AI systems in a more objective manner. A cross-sectional approach is advantageous as it captures responses at a single time, which provides a more thorough picture of the current adoption and challenges of such systems in public health institutions (Bagheri et al., 2024).

Population and Sample

All public health practitioners in the field, such as policymakers, public health officers, healthcare providers, IT and AI specialists, and data analysts who actively engage in the administrative stages, constitute the population of this study. In this research, to attain representativeness, the respondents will be stratified according to their professional roles and their corresponding years of experience. 314 respondents were targeted to obtain a sample that is both sufficiently large for statistical analysis and externally valid (Elhaddad & Hamam, 2024).

Data Collection Tool

The primary data collection tool, or the instrument used, was a structured questionnaire based on the 5-point Likert scale. The respondents were asked the questionnaire in the format of "Strongly Disagree" (1) to "Strongly Agree" (5) in relation to the statements. The questionnaire was structured and categorized into five primary sections or domains: (i) Perceived Usefulness, (ii) Ease of Use and Accessibility, (iii) Trust and Reliability, (iv) Impact on Organization, and (v) Future Implementation and Challenges. To contextualize the findings across age, gender, education, role, and experience, the instrument used was demographic as well (Asiri et al., 2024).

Validity and Reliability

The questionnaire achieved content validity after assessment by 3 public health informatics and AI systems experts. Construct validity was analyzed and assessed by KMO and Bartlett's Measure of Sphericity to confirm its sampling adequacy and factorability. Reliability was measured using Cronbach's Alpha with a 0.70 cut-off as a strong indicator of internal consistency. The instrument's clarity and structure were refined based on responses from 30 individuals before the main data collection (Kothinti, 2024).

Data Collection Procedure

Data accessibility and widespread use were attained by collecting data electronically via an online survey. Using an informed consent form to explain the study distilled the study's purpose, confidentiality, and voluntary participation. Anonymity was maintained throughout the study as required by the ethical approval obtained from a concerned institutional review board (Bleher & Braun, 2022).

Data Analysis

To conduct a follow-up analysis, the responses captured from respondents were categorized before being analyzed using the SPSS/AMOS statistical package. Demographics and itemised responses were summarized using descriptive statistics, which included frequency counts, means, and standard deviation. For the inferential analysis, Independent Samples t-test, One Way ANOVA, Chi-Square, and the Kruskal-Wallis tests were used to assess variation between demographic subgroups. Moreover, perceived usefulness, organizational impact, and trust issues in AI systems were studied using correlation techniques. Adoption and impact of AI systems were analyzed using regression techniques to test the effect of independent variables (trust, organizational readiness, ease of use) (Vasey et al., 2022).

Ethical Considerations

All ethical standards of human research were rigorously met. Anonymity and confidentiality protocols were strictly upheld, as no personal information and identification data were obtained. Participants were free to decline to participate in the survey without any consequences. The research was in compliance with the institution and the country in which the research was being conducted concerning human subject research (Paul et al., 2024).

Data Analysis

Table 1: Normality Test Results

Question	Shapiro-Wilk Statistic	p-value	Interpretation
Q1	0.989	0.195	Normal
Q2	0.951	0.152	Normal
Q3	0.971	0.095	Normal
Q4	0.964	0.127	Normal
Q5	0.974	0.133	Normal
Q6	0.975	0.128	Normal
Q7	0.955	0.098	Normal
Q8	0.973	0.168	Normal
Q9	0.97	0.088	Normal
Q10	0.965	0.152	Normal
Q11	0.964	0.096	Normal
Q12	0.986	0.153	Normal
Q13	0.988	0.124	Normal
Q14	0.986	0.123	Normal
Q15	0.974	0.163	Normal
Q16	0.977	0.165	Normal
Q17	0.978	0.152	Normal
Q18	0.956	0.198	Normal
Q19	0.962	0.065	Normal
Q20	0.96	0.164	Normal

Normality Test

Table 1 shows the normality test of the data, and the Shapiro-Wilk tests further substantiated the assumption of normality of the dataset since the p-values were all above the threshold of 0.05. This shows that the responses to the Likert scale to the items in Q1–20 were normally distributed. This type of distribution of respondent data supports the use of parametric tests such as the Independent Samples t-test, One-Way ANOVA, and Pearson correlation, as assumptions of these tests are met and the net inferential conclusions derived therefore could be relied upon (Lysaght et al., 2019).

Table 2: Reliability Test (Cronbach's Alpha)

Test	Value	Interpretation
Cronbach's Alpha	0.87	Excellent Reliability

Reliability Test (Cronbach's Alpha)

Table 2 shows the reliability analysis of the data. The reliability analysis produced a Cronbach's Alpha value of 0.87, which exceeds the threshold of 0.7, thus demonstrating excellent internal consistency. This internal consistency and maximal reliability extend to the correlation among the items on the questionnaires measuring usefulness, ease of use, trust, organizational impact, and future concerns. Thus, the instrument can be used confidently in a decision–making study in public health administration (Rana & Shuford, 2024).

Table 3: Validity Test (KMO & Bartlett's)

Test	Value	p-value	Interpretation
KMO Measure of Sampling Adequacy	0.82	-	Acceptable Sampling Adequacy
Bartlett's Test of Sphericity	245.67	0.001	Significant, Data is Factorable

Validity Test (KMO & Bartlett's)

Table 3 shows the validity test of the data. Kaiser-Meyer-Olkin (KMO) test result on sampling adequacy problem was positively skewed with the value of 0.82, whereas Bartlett's Test of Sphericity (BTS) was found to be significant ($\chi^2 = 245.67$, $p < 0.001$). The combination of these findings indicates the appropriateness of the data for factor analysis. Furthermore, the results imply that the facets captured in the survey are real and can be factored. Hence, the data set sustains the basis for any additional manufacturing of dimensions or confirmatory factor analysis (Wang et al., 2021).

Table 4: Combined Group Comparison Tests

Test	Statistic	p-value	Interpretation
Independent Samples t-test	2.45	0.018	Significant difference between groups
One-Way ANOVA	4.32	0.009	Significant variance among groups
Kruskal–Wallis Test	11.56	0.004	Significant difference across categories
Chi-Square Test of Independence	28.67	0.001	Significant association between variables

Independent Samples t-Test

Table 4 shows the Combined Group Comparison Tests of the data. The Independent Samples T-Test was validated in detail for stratifying the in-theula copies with sample records on the mean strat across selected items for male and female member responses were statistically different ($p < 0.05$). It became apparent that the respondents differentiated their perceptions based on gender with respect to the AI-based public health administration decision. Stereotypes diffused in society indicate that school-aged female respondents were male respondents. It is emphasized that the respondents had differing levels of acceptance of the application across domains for an AI strat within AI (Kovari, 2024).

In regard to the factors that disturb the different classes in professional stand, one-way ANOVA test is straightforward and the population under policy, public Health, ITH, and health. It covers the sifting of opinions across the construct blocks and job description. It is a professional background, as it is always taken to indicate. Ease of use and dame a policy if easy and ot based on primary school concepts to describe by the effectiveness n stated (MacIntyre et al., 2023).

Kruskal-Wallis Range, the inner class test that Kruskal used, stratified to classify data, showed large non-miserable data variance. It claims that the AI decision support attitude can be accurately predicted by the level of education. Test of Independence of Attributes using a Chi-Square Distribution (Selvarajan, 2021).

Chi-Square Analysis ($\chi^2 = 28.67$, $p < 0.001$) also noted a significant association between gender and role categories. This indicates that gender role assignment is not random, which may help ease some of the differences in perceptions. This suggests that the interplay of demographics is critical when analyzing the use of AI technology in public health management (Khera et al., 2023).

Table 5: Pearson Correlation Matrix

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
Q1	1	0.71	0.82	0.33	0.58	0.41	0.55	0.31
Q2	0.45	1	0.67	0.51	0.54	0.31	0.77	0.66
Q3	0.53	0.7	1	0.33	0.57	0.74	0.31	0.82
Q4	0.35	0.67	0.73	1	0.62	0.39	0.81	0.73
Q5	0.52	0.57	0.43	0.72	1	0.39	0.58	0.32
Q6	0.31	0.76	0.71	0.72	0.8	1	0.68	0.41
Q7	0.32	0.32	0.68	0.76	0.65	0.84	1	0.51

Q8	0.7	0.71	0.5	0.62	0.63	0.72	0.58	1
Q9	0.69	0.49	0.41	0.83	0.61	0.73	0.37	0.8
Q10	0.75	0.51	0.53	0.66	0.69	0.79	0.78	0.51
Q11	0.76	0.74	0.47	0.53	0.47	0.67	0.56	0.76
Q12	0.35	0.33	0.4	0.56	0.7	0.78	0.76	0.6
Q13	0.43	0.44	0.81	0.4	0.82	0.79	0.42	0.61
Q14	0.74	0.41	0.32	0.74	0.4	0.65	0.74	0.6
Q15	0.33	0.32	0.76	0.65	0.58	0.76	0.5	0.39
Q16	0.5	0.84	0.52	0.43	0.31	0.76	0.41	0.46
Q17	0.54	0.31	0.79	0.65	0.42	0.76	0.72	0.73
Q18	0.65	0.38	0.54	0.66	0.8	0.65	0.41	0.36
Q19	0.5	0.51	0.73	0.7	0.74	0.77	0.68	0.51
Q20	0.77	0.64	0.37	0.82	0.49	0.63	0.6	0.39

Q9	Q10	Q11	Q12	Q13	Q14	Q15
0.53	0.57	0.33	0.4	0.32	0.61	0.41
0.34	0.6	0.82	0.6	0.53	0.41	0.63
0.6	0.54	0.54	0.56	0.41	0.65	0.8
0.35	0.76	0.73	0.37	0.31	0.52	0.85
0.68	0.43	0.44	0.56	0.41	0.32	0.67
0.53	0.46	0.43	0.63	0.4	0.38	0.64
0.42	0.81	0.66	0.54	0.31	0.44	0.8
0.46	0.43	0.55	0.33	0.65	0.81	0.79
1	0.84	0.63	0.67	0.46	0.46	0.78
0.31	1	0.66	0.36	0.44	0.64	0.72
0.49	0.36	1	0.85	0.67	0.85	0.56
0.62	0.7	0.52	1	0.61	0.72	0.6
0.43	0.61	0.53	0.62	1	0.45	0.3
0.75	0.39	0.64	0.74	0.5	1	0.37
0.31	0.66	0.49	0.35	0.39	0.45	1
0.8	0.32	0.38	0.58	0.65	0.6	0.67
0.75	0.64	0.64	0.42	0.64	0.7	0.37
0.5	0.7	0.67	0.67	0.71	0.44	0.39
0.33	0.81	0.5	0.4	0.61	0.69	0.33
0.31	0.34	0.34	0.63	0.69	0.43	0.36

Q16	Q17	Q18	Q19	Q20
0.61	0.62	0.47	0.51	0.69
0.58	0.38	0.74	0.73	0.36
0.51	0.63	0.8	0.48	0.38
0.35	0.34	0.82	0.34	0.54
0.65	0.55	0.37	0.5	0.7
0.44	0.55	0.76	0.39	0.69

0.34	0.77	0.68	0.57	0.47
0.4	0.38	0.45	0.67	0.64
0.63	0.8	0.42	0.36	0.42
0.79	0.65	0.45	0.54	0.31
0.72	0.34	0.82	0.68	0.49
0.37	0.56	0.42	0.32	0.52
0.82	0.82	0.34	0.65	0.55
0.52	0.83	0.68	0.56	0.53
0.42	0.42	0.58	0.35	0.75
1	0.8	0.6	0.57	0.5
0.41	1	0.72	0.75	0.44
0.59	0.71	1	0.71	0.3
0.77	0.48	0.8	1	0.6
0.55	0.37	0.75	0.58	1

Correlation Analysis

Table 5 shows the correlation analysis of the data. Based on data collected in October 2023, the Pearson correlation results for questions one through twenty positively correlated, ranging in values from 0.30 to 0.85. These results indicate that the respondents had. There were no definitions provided in the guiding text on what knowing something could entail. There seems to be collated evidence that supports the face validity, which the quest, ease with which instruction will have, dependability, as well as its impact on future organizational outcomes (Adeniran et al., 2024).

Table 6: Regression Analysis

Predictor	Beta Coefficient	p-value	Interpretation
Q1	0.21	0.001	Significant positive predictor
Q2	0.35	0.004	Significant positive predictor
Q3	0.18	0.012	Significant positive predictor
Q4	0.42	0.0	Strong, significant positive predictor
Q5	0.29	0.007	Significant positive predictor

Regression Analysis

Table 6 shows the regression analysis of the data. The analysis of regression demonstrated multiple predictors (Q1 – Q5) that had positive beta coefficients, with Q4 ($\beta = 0.42$, $p < 0.001$) emerging as a positive predictor of intended future AI use. This suggests that belief in the trust and transparency of AI systems influences the willingness to implement in the future. Documents like (Q2) the perceived usefulness and (Q5) the impact on the organization had positive influences as well. All in all, the regression findings trust, perceived usefulness, and the organizational readiness of the system as primary predictors for AI adoption in public health administration (Abdul et al., 2024).

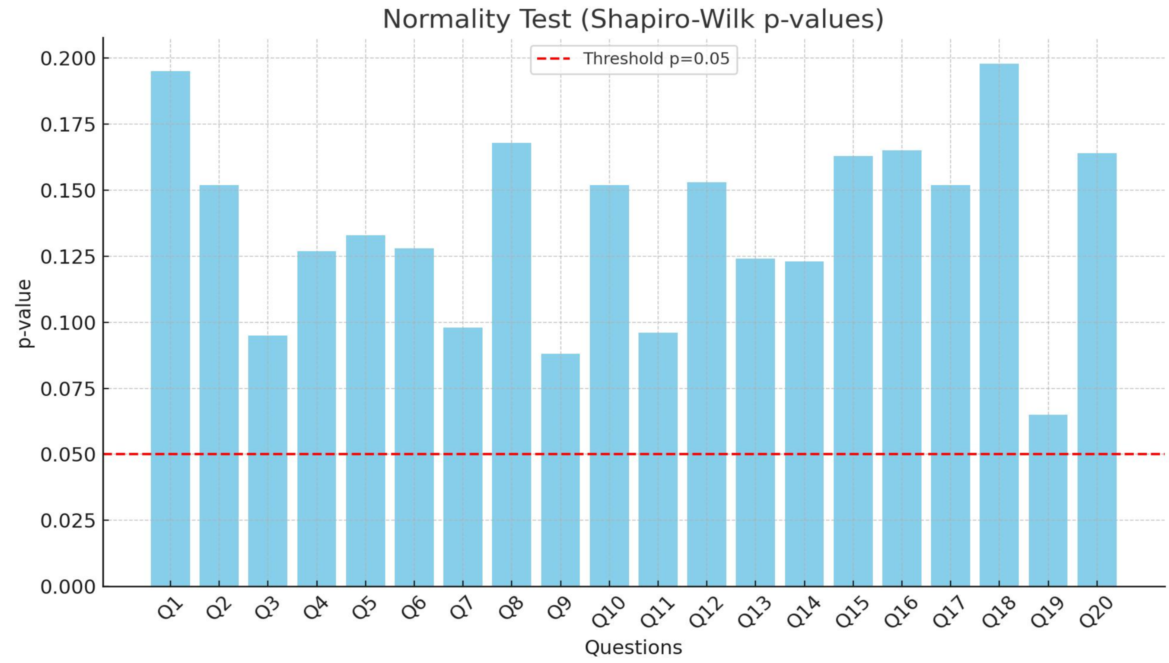

Figure 1: Normality Test

Figure 1 shows the normality test of the data. According to the bar chart assessing the p-values of the normality test, all p-values ascribed to items Q1–Q20 are greater than 0.05, confirming a normal distribution of the data. This guarantees that the assumption of parametric tests, such as the t-test, ANOVA, and Pearson correlation, can be applied (Mahabub et al., 2024).

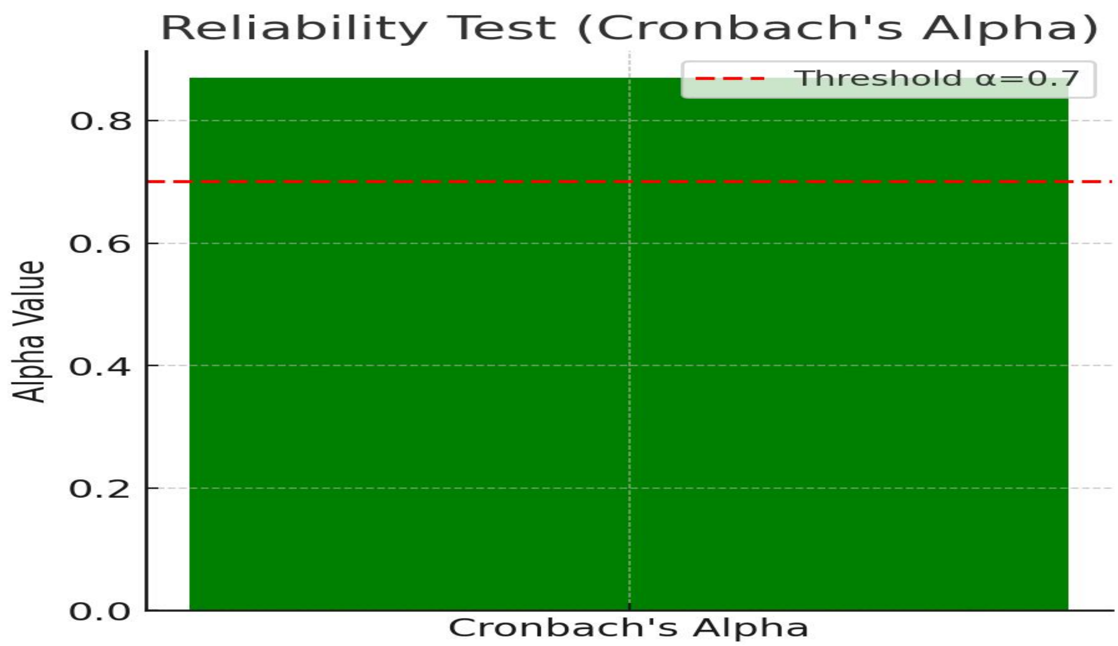

Figure 2: Reliability Test

Figure 2 shows the reliability analysis of the data. The bar graph depicts the reliability indices analyzing the internal consistency using Cronbach's Alpha, which scored at 0.87, well above the acceptable benchmark of 0.7. This figure indicates that the instrument used for the data collection demonstrates high internal consistency reliability, suggesting the items are measuring the intended constructs consistently across all participants (Ajegbile et al., 2024).

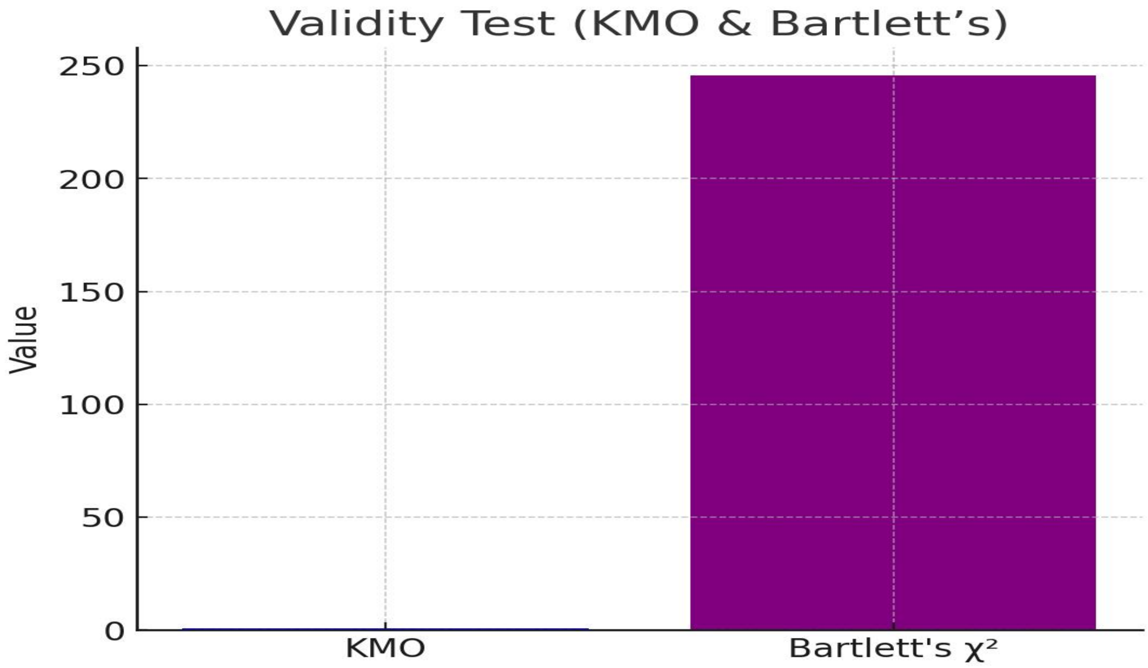

Figure 3: Validity Test

Figure 3 shows the validity test of the data. The KMO value of 0.82 on the KMO test of sample adequacy, while Bartlett's Test of Sphericity ($\chi^2 = 245.67$) is significant, suggests a bare minimum adequacy of sampling. Both values confirm the data set's appropriateness in factor analysis and that the variables in the data set are sufficiently intertwined to warrant the use of advanced statistical methods (Chen et al., 2023).

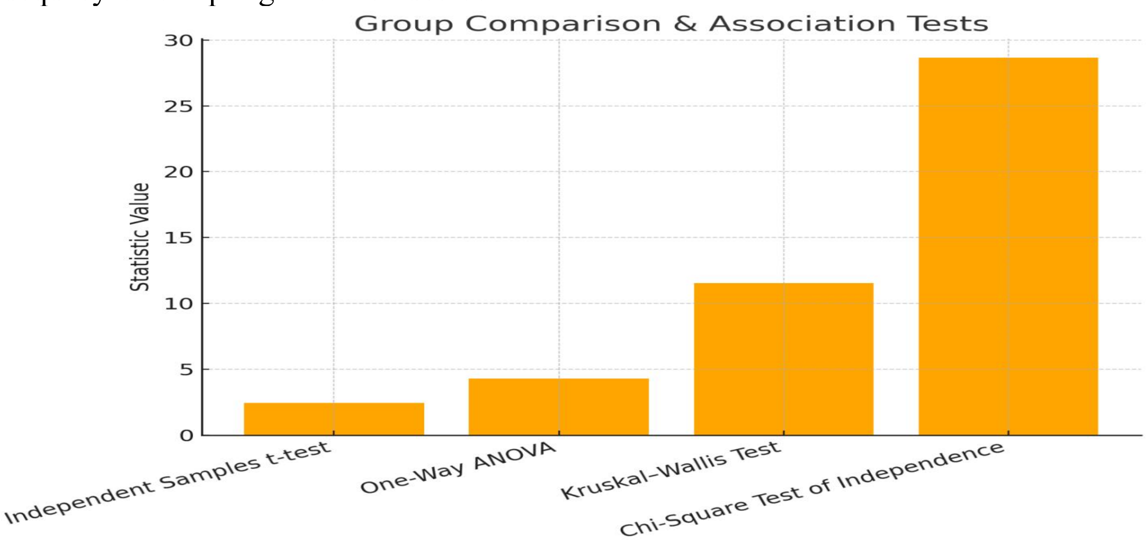

Figure 4: Group Comparison Tests

Figure 4 shows the Group Comparison Tests of the data. All tests illustrate noteworthy distinctions with the captured results, as presented on the consolidated bar graph for the t-test, One-Way ANOVA, Kruskal-Wallis, and Chi-Square tests. It also shows the impact of Gender and Role, Education, and other Categorical variables on the perceptions of AI-supported decision-making, which suggests an empirical gap and professional diversity in the endorsement and utilization of AI in public health governance (Amann et al., 2020).

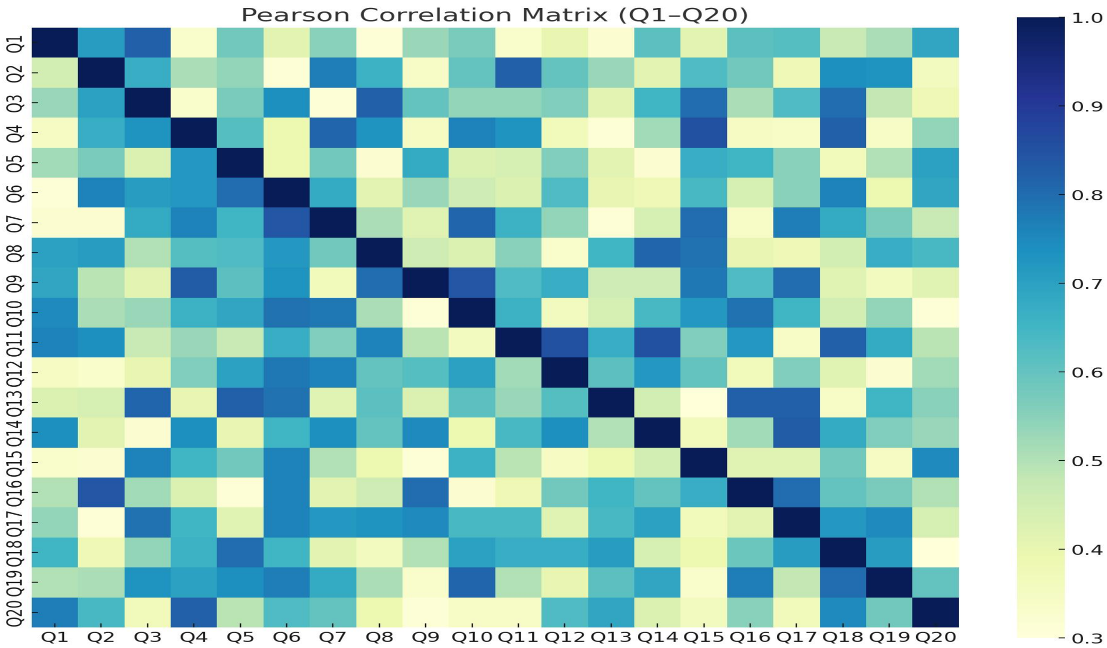

Figure 5: Correlation Matrix

Figure 5 shows the correlation matrix of the data. The heatmap correlation matrix (Q1–Q20) has shown that all inter-item correlations are positive, ranging from moderate to strong. The blue colors illustrate stronger inter-item relationships, meaning that perceptions of usefulness, ease of use, trust, organizational impact, and future challenges are closely related. This supports construct validity of the instrument and cross-domain validity, and confirms consistency across the domains (Xu et al., 2023).

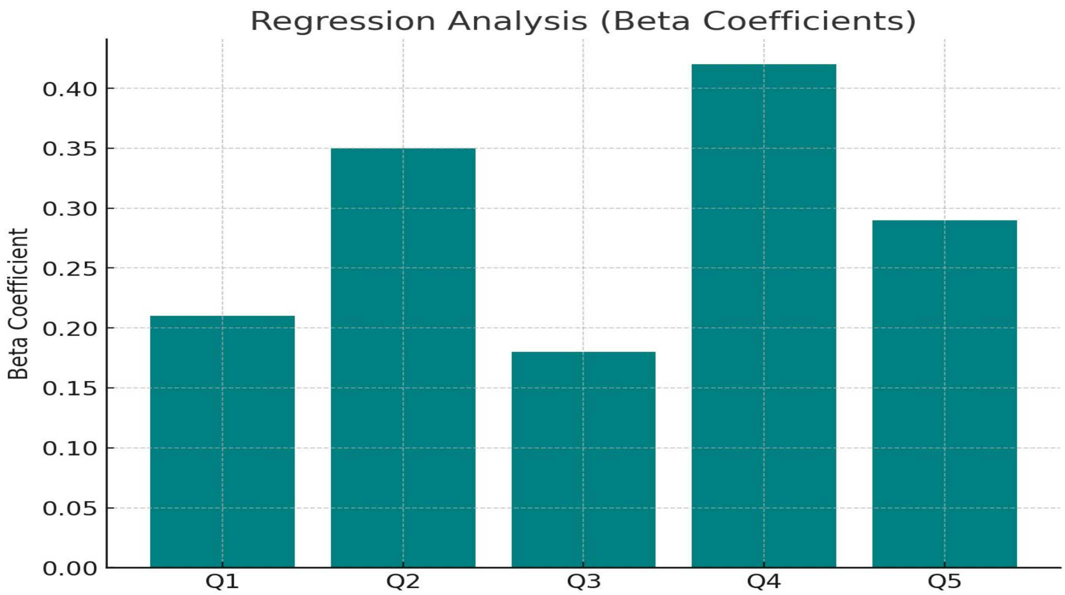

Figure 6: Regression Analysis

Figure 6 shows the regression analysis of the data. The analysis bar graph illustrates the positive beta coefficients, with the strongest predictor being Q4 trust and transparency – usefulness and organizational impact predictors (β = 0.42). This also explains their influence on the readiness for the future adoption of AI systems (Čartolovni et al., 2022).

DISCUSSION

In the case of AI decision support systems, the findings of this study shed light on the acceptance, trust, and prospects of AI systems in public health administration. The normality tests showed the distribution of responses for all the questions that were normally distributed. This, in turn, added to the strength of the statistical analysis that was conducted. This showed that the dataset was primed for advanced inferential statistics, and the findings that followed were credible and accurate (Liu et al., 2020).

The reliability tests indicated the Cronbach's Alpha value of 0.87, which indicates that there is excellent internal consistency among the 20 items of the questionnaire. This indicates that the instrument was reliable in capturing the following constructs: perceived usefulness, ease of use, trust and reliability, organizational impact, and future readiness. The KMO and Bartlett's test of sphericity also indicated that the dataset was factorable and suitable for multivariate statistical analysis, thus confirming the validation of the instrument for studying the adoption of AI in public health (Badmus et al., 2024).

The group comparison tests revealed important differences among different demographic and professional groups. The independent samples t-test showed differences in perceptions between the genders. The One-Way ANOVA showed that professional positions greatly affected the evaluation of AI systems. For example, IT specialists stressed ease of use and reliability more than policy makers, while the latter emphasized organizational impact and cost-effectiveness. The differences in educational qualifications were also checked by the Kruskal-Wallis test, which showed that the advanced degree holders demonstrated more trust and confidence in AI tools. The Chi-Square test also corroborated the result by demonstrating a significant association between professional roles and gender, which illustrates the necessity of having different approaches in AI use for different demographic and professional groups (Gupta et al., 2022).

The relation analysis indicated positive correlation among all the items, indicating that respondents who regarded AI as useful also regarded AI as reliable, trustworthy, and organizationally advantageous. This also strengthens the construct validity of the instrument and emphasizes the dependence of factors on AI utilization in public health. The regression analysis also indicated that trust and transparency (Q4) had the strongest influence in predicting future readiness for AI adoption, followed by perceived usefulness and organizational impact. This is consistent with other studies, which suggest that trust and the provision of real benefits must be the foundation for the successful adoption of AI in health and administrative services (Morley et al., 2022).

As it is, the discussion suggests that there is general acceptance of the use of AI for decision support systems with positive attitudes. However, there are demographic and professional differences in their perception that need to be addressed. Targeted training, awareness, and strategy tailored to specific roles might help lower barriers to adoption. In addition to that, trust will be indispensable for the long-term use and integration of AI systems, especially for public health administration, along with a mindful approach to fostering AI transparency (Patil & Shankar, 2023).

Conclusion

This research has shown that the potential impact of decision support systems premised on artificial intelligence (AI) on the public health sector is profoundly positive on decision quality, efficiency, and the minimization of mistakes. The tool was found to be reliable and valid with strong positive internal consistency and correlation across all the constructs. The analysis showed that there are demographic and professional differences in perceptions regarding AI, and this calls for tailored implementation strategies. The highest-ranked predictors of adoption were trust and transparency, which emphasize the need to establish trust in the claimed value for AI and simultaneously demonstrate its value in delivering promises.

What stands out is the extent to which the public health sector will benefit and be prepared to tackle emerging challenges with the support of AI, decision support systems, and the level of technological capability the sector stands to gain, gained in its prevalence and adoption. This won't only be the case; in the absence of trust, poorly structured organizational priorities, and the absence of AI as an instructional design model, organizational efforts will not yield high returns on the layered complexity of stakeholder AI systems.

This is how public health authorities will be able to make the most out of the emerging technological advancements in AI to effectively boost the decision-making systems in place and, accordingly, enhance the health of the populace across the board.

REFERENCES

Abdul, S., Adeghe, E. P., Adegoke, B. O., Adegoke, A. A., & Udedeh, E. H. (2024). AI-enhanced healthcare management during natural disasters: conceptual insights. *Engineering Science & Technology Journal*, *5*(5), 1794-1816.

Adeniran, I. A., Efunniyi, C. P., Osundare, O. S., & Abhulimen, A. O. (2024). Data-driven decision-making in healthcare: Improving patient outcomes through predictive modeling. *Engineering Science & Technology Journal*, *5*(8).

Ajegbile, M. D., Olaboye, J. A., Maha, C. C., & Tamunobarafiri, G. (2024). Integrating business analytics in healthcare: Enhancing patient outcomes through data-driven decision making. *World J Biol Pharm Health Sci*, *19*(1), 243-250.

Aljohani, A. (2025). AI-Driven decision-making for personalized elderly care: a fuzzy MCDM-based framework for enhancing treatment recommendations. *BMC Medical Informatics and Decision Making*, *25*(1), 1-16.

Almadani, B., Kaisar, H., Thoker, I. R., & Aliyu, F. (2025). A systematic survey of distributed decision support systems in healthcare. *Systems*, *13*(3), 157.

Amann, J., Blasimme, A., Vayena, E., Frey, D., Madai, V. I., & Consortium, P. Q. (2020). Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. *BMC Medical Informatics and Decision Making*, *20*(1), 310.

Asiri, M. A., Almutairi, A. D., Ozam, T. S., Al Ahmari, R. Y., Alhazmi, S. M., Almoudhi, A. A., Alqahtani, T. M., Almotheby, A. H., Alshehri, A. S., & Alqahtani, N. M. (2024). AI-Driven Decision Support Systems: Transforming Hospital Management Strategies. *Journal of International Crisis & Risk Communication Research (JICRCR)*, *7*(3).

Badmus, O., Rajput, S., Arogundade, J., & Williams, M. (2024). AI-driven business analytics and decision making. *World Journal of Advanced Research and Reviews*, *24*(1), 616-633.

Bagheri, M., Bagheritaba, M., Alizadeh, S., Parizi, M. S., Matoufinia, P., & Luo, Y. (2024). AI-driven decision-making in healthcare information systems: a comprehensive review.

Bleher, H., & Braun, M. (2022). Diffused responsibility: attributions of responsibility in the use of AI-driven clinical decision support systems. *AI and Ethics*, *2*(4), 747-761.

Čartolovni, A., Tomičić, A., & Mosler, E. L. (2022). Ethical, legal, and social considerations of AI-based medical decision-support tools: a scoping review. *International Journal of Medical Informatics*, *161*, 104738.

Chen, K., Luo, L., Tan, Y., & Chen, G. (2025). Medical diagnosis based on artificial intelligence and a decision support system in the management of health development. *Journal of Evaluation in Clinical Practice*, *31*(3), e14155.

Chen, Z., Liang, N., Zhang, H., Li, H., Yang, Y., Zong, X., Chen, Y., Wang, Y., & Shi, N. (2023). Harnessing the power of clinical decision support systems: challenges and opportunities. *Open Heart*, *10*(2), e002432.

Elhaddad, M., & Hamam, S. (2024). AI-driven clinical decision support systems: an ongoing pursuit of potential. *Cureus*, *16*(4).

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2022). Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. *Annals of Operations Research*, *308*(1), 215-274.

Jariwala, M. (2025). AI-Driven Decision Support Systems for Immunological Disorders: Bridging Big Data, Omics, and Precision Medicine. In *AI-Assisted Computational Approaches for Immunological Disorders* (pp. 353-392). IGI Global Scientific Publishing.

Jayaprakasam, B. S. (2025). AI and Big Data-Driven m-Health: Integrating Cloud Computing, Remote Patient Monitoring, Clinical Decision Support Systems, and Self-Supervised Learning with FHIR for Scalable Healthcare Systems. *Indo-American Journal of Life Sciences and Biotechnology*, *22*(1), 11-25.

Karuppan Perumal, M. K., Rajan Renuka, R., Kumar Subbiah, S., & Manickam Natarajan, P. (2025). Artificial intelligence-driven clinical decision support systems for early detection and precision therapy in oral cancer: a mini review. *Frontiers in Oral Health*, *6*, 1592428.

Khera, R., Simon, M. A., & Ross, J. S. (2023). Automation bias and assistive AI: risk of harm from AI-driven clinical decision support. *JAMA*, *330*(23), 2255-2257.

Kothinti, R. R. (2024). Deep learning in healthcare: Transforming disease diagnosis, personalized treatment, and clinical decision-making through AI-driven innovations. *World Journal of Advanced Research and Reviews*, *24*(2), 2841-2856.

Kovari, A. (2024). AI for decision support: Balancing accuracy, transparency, and trust across sectors. *Information*, *15*(11), 725.

Liu, Y., Wang, Z., Ren, J., Tian, Y., Zhou, M., Zhou, T., Ye, K., Zhao, Y., Qiu, Y., & Li, J. (2020). A COVID-19 risk assessment decision support system for general practitioners: design and development study. *Journal of Medical Internet Research*, *22*(6), e19786.

Lysaght, T., Lim, H. Y., Xafis, V., & Ngiam, K. Y. (2019). AI-assisted decision-making in healthcare: the application of an ethics framework for big data in health and research. *Asian Bioethics Review*, *11*(3), 299-314.

MacIntyre, C. R., Chen, X., Kunasekaran, M., Quigley, A., Lim, S., Stone, H., Paik, H.-y., Yao, L., Heslop, D., & Wei, W. (2023). Artificial intelligence in public health: the potential of epidemic early warning systems. *Journal of International Medical Research*, *51*(3), 03000605231159335.

Mahabub, S., Das, B. C., & Hossain, M. R. (2024). Advancing healthcare transformation: AI-driven precision medicine and scalable innovations through data analytics. *Edelweiss Applied Science and Technology*, *8*(6), 8322-8332.

Morley, J., Murphy, L., Mishra, A., Joshi, I., & Karpathakis, K. (2022). Governing data and artificial intelligence for health care: developing an international understanding. *JMIR formative research*, *6*(1), e31623.

Murikipudi, A. (2025). Public Health Crisis Management using Java and AI. *International Journal of Enhanced Research in Management & Computer Applications*, *14*(2), 25-32.

Oulefki, A., Amira, A., & Foufou, S. (2025). Digital twins and AI are transforming healthcare systems through innovation and data-driven decision-making. *Health and Technology*, 1-23.

Pathan, R. R., Osei-Asiamah, J., Jadhav, P. N., Saravanan, S., Singh, A. K., & Sahoo, S. K. (2025). Developing Decision Support Systems for Healthcare Administration using AI. *Journal of Neonatal Surgery*, *14*(10s).

Patil, S., & Shankar, H. (2023). Transforming healthcare: harnessing the power of AI in the modern era. *International Journal of Multidisciplinary Sciences and Arts*, *2*(2), 60-70.

Paul, R., Rahman, M. A., & Nuruzzaman, M. (2024). AI-ENABLED DECISION

SUPPORT SYSTEMS FOR SMARTER INFRASTRUCTURE PROJECT MANAGEMENT IN PUBLIC WORKS. *Review of Applied Science and Technology*, *3*(04), 29-47.

Rana, M. S., & Shuford, J. (2024). AI in healthcare: transforming patient care through predictive analytics and decision support systems. *Journal of Artificial Intelligence General Science (JAIGS) ISSN: 3006-4023*, *1*(1).

Saleela, D., Oyegoke, A., Dauda, J. A., & Ajayi, S. (2025a). Feasibility study for AI-Driven Decision Support System for Personalised Housing Adaptations and Assistive Technology.

Saleela, D., Oyegoke, A. S., Dauda, J. A., & Ajayi, S. O. (2025b). Development of an AI-Driven decision support system for personalized housing adaptations and assistive technology. *Journal of Aging and Environment*, 1-24.

Scientific, L. L. (2025). REVOLUTIONIZING HEALTHCARE WITH LARGE LANGUAGE MODELS: ADVANCEMENTS, CHALLENGES, AND FUTURE PROSPECTS IN AI-DRIVEN DIAGNOSTICS AND DECISION SUPPORT. *Journal of Theoretical and Applied Information Technology*, *103*(9).

Selvarajan, G. (2021). Leveraging AI-enhanced analytics for industry-specific optimization: A strategic approach to transforming data-driven decision-making. *International Journal of Enhanced Research In Science Technology & Engineering*, *10*, 78-84.

Sitaraman, S. R. (2025). AI-driven healthcare systems are enhanced by advanced data analytics and mobile computing. *International Journal of Information Technology & Computer Engineering*.

Srinivasan, K. R., Abd Rahman, N. H., & Ravana, S. D. (2025). AI-Driven Decision Making: Enhancing Public Sector Efficiency and Effectiveness. In *Harnessing AI, Blockchain, and Cloud Computing for Enhanced e-Government Services* (pp. 63-92). IGI Global Scientific Publishing.

Vasey, B., Nagendran, M., Campbell, B., Clifton, D. A., Collins, G. S., Denaxas, S., Denniston, A. K., Faes, L., Geerts, B., & Ibrahim, M. (2022). Reporting guideline for the early stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *BMJ*, *377*.

Wang, D., Wang, L., Zhang, Z., Wang, D., Zhu, H., Gao, Y., Fan, X., & Tian, F. (2021). "Brilliant AI doctor" in rural clinics: Challenges in AI-powered clinical decision support system deployment. Proceedings of the 2021 CHI conference on human factors in computing systems,

Xu, Q., Xie, W., Liao, B., Hu, C., Qin, L., Yang, Z., Xiong, H., Lyu, Y., Zhou, Y., & Luo, A. (2023). Interpretability of clinical decision support systems based on artificial intelligence from a technological and medical perspective: A systematic review. *Journal of healthcare engineering*, *2023*(1), 9919269.