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ARTIFICIAL INTELLIGENCE GOVERNANCE READINESS AND RESPONSIBLE ADOPTION AMONG HEALTH ADMINISTRATION AND HEALTH INFORMATION PROFESSIONALS: A MULTICENTER CROSS-SECTIONAL STUDY

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ABSTRACT

Health systems are adopting artificial intelligence (AI) faster than many organizations are developing the policies, workforce capability, data controls, and monitoring processes needed to govern it safely. Health administration and health information professionals are central to procurement, data stewardship, workflow design, quality oversight, and implementation, yet their readiness for responsible AI adoption remains underexamined. To propose and test an analysis framework for assessing AI governance readiness and responsible adoption among health administration and health information/informatics professionals across multiple Saudi healthcare organizations. A multicenter cross-sectional survey design was specified for six coded healthcare institutions across three Saudi regions. The proposed 31-item instrument covers governance readiness, data and technical readiness, workforce AI capability, responsible AI climate, perceived value, and responsible adoption. Because field data have not yet been collected, a synthetic dataset of 432 complete records was generated solely to test scoring, reliability, tables, figures, and regression procedures. Analyses included frequencies, means with 95% confidence intervals (CIs), Cronbach alpha, group comparisons, Spearman correlations, and multivariable linear regression with center fixed effects and HC3 robust standard errors. In the sample, 241 (55.8%) records represented health administration professionals and 191 (44.2%) represented health information/informatics professionals. Proposed high governance readiness was observed in 119 (27.5%) records. Mean scores ranged from 2.97 (SD 0.75) for governance readiness to 3.45 (SD 0.80) for perceived value; Cronbach alpha ranged from 0.80 to 0.85. Health information/informatics records had higher

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workforce capability (3.46 vs 3.20; p=0.001), responsible adoption (3.45 vs 3.28; p=0.031), and overall readiness (3.18 vs 3.07; p=0.037). In the adjusted model, responsible AI climate (B=0.204 per SD, p<0.001), workforce capability (B=0.167, p<0.001), perceived value (B=0.159, p<0.001), governance readiness (B=0.133, p=0.001), data and technical readiness (B=0.079, p=0.020), and prior AI use (B=0.159, p=0.019) were positively associated with responsible adoption. Adjusted R2 was 0.425. The prototype demonstrates a coherent way to measure and analyze AI governance readiness in the healthcare administrative and information workforce. The simulated pattern suggests a potentially important gap between perceived AI value and operational governance capacity, but no prevalence or association should be interpreted as an empirical finding. Real-world content validation, pilot testing, ethics approval, and multicenter data collection are required before scientific submission.

KEYWORDS: Artificial Intelligence; Governance; Responsible AI; Health Administration; Health Information Management; Organizational Readiness; Saudi Arabia; Cross-Sectional Study.

1. INTRODUCTION

Artificial intelligence is increasingly embedded in clinical decision support, operational forecasting, scheduling, coding, population health, documentation, and patient communication. Its potential benefits are substantial, but healthcare AI can also create new risks through biased data, weak generalizability, opaque outputs, privacy breaches, automation bias, performance drift, and unclear accountability. The World Health Organization (WHO) therefore places autonomy, safety, transparency, accountability, equity, and sustainability at the center of AI for health [1,2].

Governance is the organizational mechanism that translates these principles into decisions and controls. It includes written policy, multidisciplinary oversight, risk classification, procurement assurance, local validation, incident reporting, performance monitoring, and the ability to modify or suspend unsafe systems. The NIST AI Risk Management Framework expresses a similar operational logic through the functions govern, map, measure, and manage [5,15]. Saudi guidance adds a nationally relevant layer: the Saudi Data & AI Authority's AI Ethics Principles apply to AI stakeholders in the Kingdom, while the Personal Data Protection Law treats health data as sensitive and requires organizational, administrative, and technical safeguards [3,4].

Recent evidence emphasizes that governance must be practical, lifecycle-based, and sociotechnical. A 2026 scoping review identified four recurring components of healthcare AI governance frameworks: guiding principles, assessment methods, lifecycle stages, and oversight mechanisms [6]. Yet many frameworks remain fragmented or have not been evaluated in real organizational settings. Consensus guidance such as FUTURE-AI similarly emphasizes fairness, universality, traceability, usability, robustness, and explainability across the AI lifecycle [8].

The workforce is a decisive part of this system. Health administrators influence strategy, procurement, budgeting, quality, change management, and accountability. Health information and informatics professionals influence data quality, interoperability, privacy, system integration, terminology, analytics, and performance monitoring. AI-capable organizations need both groups to coordinate with clinicians, information technology teams, legal advisers, safety officers, and patients [9]. Reviews of healthcare AI adoption consistently identify trust, training, workflow fit, infrastructure, leadership, regulation, and governance as interacting barriers or facilitators [10].

Available surveys often focus on physicians, nurses, or students and tend to measure general attitudes, perceived usefulness, or educational readiness. The Shinners Artificial Intelligence Perception tool provided an early validated approach to workforce perception [11], while readiness scales have been developed for medical trainees [13]. Saudi evidence also indicates that computer skills, AI knowledge, informatics involvement, and prior technology experience shape perceptions of AI [12]. However, there remains a specific gap concerning governance readiness and responsible adoption among administrative and health information professionals across institutions.

Accordingly, this study was designed to assess AI governance readiness and responsible adoption among these two professional groups in Saudi healthcare organizations. The primary objective is to estimate domain scores and identify organizational and individual factors associated with responsible adoption. Secondary objectives are to compare the two professional groups, examine the internal consistency and construct relationships of the proposed questionnaire, and identify practical priorities for governance, education, and implementation. In the current prototype, synthetic data are used only to test whether this design and analysis pipeline produce coherent and auditable outputs.

2. METHODS

2.1. Study Design and Proposed Setting

The field study is planned as a multicenter cross-sectional survey. The prototype assumes six healthcare institutions coded A through F, distributed across the Central, Western, and Eastern regions of Saudi Arabia and representing public tertiary, public specialist, and private hospital settings. The center labels are placeholders; actual participating organizations must be confirmed through formal approvals and site agreements. Reporting is structured with reference to the STROBE statement for cross-sectional studies [16].

2.2. Population And Eligibility

The target population comprises employed health administration and health information/informatics professionals whose roles contribute to management, data governance, quality, digital health, analytics, health records, informatics, privacy, or technology-enabled service delivery. Eligible participants should be adults currently working at a participating organization, have at least six months of employment

at that site, and be able to provide informed consent. Students without an employment role, professionals outside the two target disciplines, vendor representatives, and respondents who do not complete the primary outcome items should be excluded.

2.3. Sample Size and Sampling

For a conservative prevalence estimate of 50%, 95% confidence, and 5% absolute precision, a simple random sample requires approximately 384 analyzable responses. Allowing 15% for incomplete or unusable submissions yields a recruitment target of approximately 452. The final target should be increased if clustering, center-level comparisons, or psychometric split-sample analyses are primary objectives. Proportionate allocation by institution and profession is preferable. If probability sampling is not operationally feasible, stratified quota-based convenience sampling should be used and clearly disclosed.

2.4. Questionnaire Development

The proposed instrument contains 31 statements rated from 1 (strongly disagree) to 5 (strongly agree). Item content was mapped to WHO ethics and regulatory guidance [1,2], Saudi AI ethics and data-protection requirements [3,4], the NIST AI RMF [5], recent healthcare governance frameworks [6-8,14], and workforce-adoption literature [9-13,17]. The six domains are governance readiness (6 items), data and technical readiness (5), workforce AI capability (5), responsible AI climate (6), perceived value (4), and responsible adoption (5). The full wording appears in Appendix A and in the companion analysis workbook.

Before field use, the English instrument should undergo multidisciplinary content review by experts in health administration, health informatics, AI governance, ethics, psychometrics, quality and safety, and Saudi data protection. For Arabic use, forward translation, reconciliation, back-translation, cognitive debriefing, and bilingual review are required. A pilot of approximately 30-50 eligible professionals should assess comprehension, completion time, floor or ceiling effects, missingness, and preliminary reliability. Content validity indices and exploratory or confirmatory factor analysis should be reported only after real validation work has been completed.

2.5. Variables And Scoring

Demographic and professional variables include center, region, institution type, professional group, gender, age group, education, years of experience, managerial role, formal AI training, prior professional AI use, and computer proficiency. Each domain score is calculated as the mean of its completed items, preserving the 1-5 scale. Responsible adoption is the primary continuous outcome. Overall governance readiness is the mean of governance readiness, data and technical readiness, workforce AI capability, and responsible AI climate. A score of 3.50 or higher is used as a proposed descriptive threshold for high readiness; this threshold is not validated and should be tested in sensitivity analyses.

2.6. Synthetic Dataset Generation

Because no field responses were available, a deterministic synthetic dataset was generated with a fixed random seed (20260810). The dataset contains 432 complete records distributed across six coded centers. Demographic variables were sampled from plausible distributions, and correlated latent variables were used to generate Likert item responses. Group and training effects were introduced only to exercise the intended statistical tests. No synthetic record corresponds to a real person, no patient or employee data were accessed, and the resulting coefficients are not estimates of real-world effects.

2.7. Statistical Analysis

Categorical variables were summarized as frequency and percentage; continuous construct scores were summarized as mean, standard deviation, and 95% CI. Cronbach alpha assessed internal consistency within each proposed domain. Professional-group differences were examined using Welch independent-samples t tests with mean differences and Cohen d. Categorical distributions were compared with chi-square tests. Spearman coefficients described associations among construct scores.

The primary model was a multivariable linear regression with responsible adoption as the outcome. Continuous construct predictors were standardized, so each coefficient represents the expected change in the 1-5 adoption score for a one-standard-deviation increase. The model included governance readiness, data and technical readiness, workforce AI capability, responsible AI climate, perceived value, profession, formal AI training, prior AI use, managerial role, experience categories, and center fixed effects. HC3 robust standard errors were used. Two-sided p values below 0.05 were considered statistically significant. Center coefficients were

treated as adjustment terms and are omitted from the compact manuscript table. Analyses were implemented in Python using NumPy, pandas, and SciPy; the full synthetic data, scoring rules, and outputs are retained in the companion workbook.

2.8. Ethics And Data Governance

No human participants, identifiable records, or institutional operational data were used in this simulation; therefore, institutional review board approval and consent were not applicable to the prototype. The actual multicenter study must obtain ethics approval, site permission, informed consent, secure data-storage arrangements, and an approved data-management plan before recruitment. The field protocol should minimize identifiers, restrict access, define retention and destruction, address cross-site transfer, and comply with Saudi requirements for personal and health data [4].

3. RESULTS

3.1. Sample Characteristics

The analytic dataset contained 432 complete records. Health administration represented 241 (55.8%) records and health information/informatics represented 191 (44.2%). The center distribution ranged from 52 (12.0%) records at center B to 97 (22.5%) at center A. Formal AI training was present in 142 (32.9%) records, prior professional AI use in 201 (46.5%), and advanced computer proficiency in 165 (38.2%). Training, prior use, and computer proficiency differed by professional group (all $p<0.001$).

Table 1: Participant Characteristics by Professional Group.

Characteristic	Category	Total	Health administration	Health information/informatics	p value
Center	A	97 (22.5%)	48 (19.9%)	49 (25.7%)	0.426
	B	52 (12.0%)	28 (11.6%)	24 (12.6%)	
	C	87 (20.1%)	50 (20.7%)	37 (19.4%)	
	D	61 (14.1%)	37 (15.4%)	24 (12.6%)	
	E	70 (16.2%)	36 (14.9%)	34 (17.8%)	
	F	65 (15.0%)	42 (17.4%)	23 (12.0%)	
Gender	Female	221 (51.2%)	126 (52.3%)	95 (49.7%)	0.668
	Male	211 (48.8%)	115 (47.7%)	96 (50.3%)	
Age group (years)	<30	86 (19.9%)	48 (19.9%)	38 (19.9%)	0.941
	30–39	161 (37.3%)	87 (36.1%)	74 (38.7%)	
	40–49	109 (25.2%)	63 (26.1%)	46 (24.1%)	
	≥50	76 (17.6%)	43 (17.8%)	33 (17.3%)	
Highest education	Bachelor	244 (56.5%)	135 (56.0%)	109 (57.1%)	0.534
	Master	166 (38.4%)	96 (39.8%)	70 (36.6%)	
	Doctorate	22 (5.1%)	10 (4.1%)	12 (6.3%)	
Professional experience (years)	<5	99 (22.9%)	54 (22.4%)	45 (23.6%)	0.636
	5–9	107 (24.8%)	63 (26.1%)	44 (23.0%)	
	10–14	91 (21.1%)	46 (19.1%)	45 (23.6%)	
	≥15	135 (31.2%)	78 (32.4%)	57 (29.8%)	
Managerial role	No	341 (78.9%)	186 (77.2%)	155 (81.2%)	0.375
	Yes	91 (21.1%)	55 (22.8%)	36 (18.8%)	
Formal AI training	No	290 (67.1%)	185 (76.8%)	105 (55.0%)	<0.001
	Yes	142 (32.9%)	56 (23.2%)	86 (45.0%)	
Prior use of AI for work	No	231 (53.5%)	163 (67.6%)	68 (35.6%)	<0.001
	Yes	201 (46.5%)	78 (32.4%)	123 (64.4%)	
Computer proficiency	Basic	79 (18.3%)	65 (27.0%)	14 (7.3%)	<0.001
	Intermediate	188 (43.5%)	127 (52.7%)	61 (31.9%)	
	Advanced	165 (38.2%)	49 (20.3%)	116 (60.7%)	

Values are n (%). P values are from chi-square tests and appear on the first category row of each characteristic. HA, health administration; HI, health information/informatics.

3.2. Construct Scores and Internal Consistency

Perceived value had the highest mean score (3.45, SD 0.80), followed by responsible adoption (3.36, SD 0.81) and workforce AI capability (3.32, SD 0.78). Governance readiness had the lowest mean (2.97, SD 0.75). Internal consistency was acceptable to good across the proposed domains, with alpha values from 0.80 for perceived value to 0.85 for governance readiness, responsible AI climate, and responsible

adoption. These reliability estimates reflect only the imposed correlation structure of the simulation and do not validate the instrument.

Table 2: Construct Scores and Internal Consistency.

Domain	Items	Mean	SD	95% CI	Cronbach alpha
Governance readiness	6	2.96	0.75	2.89 to 3.04	0.85
Data and technical readiness	5	3.09	0.79	3.01 to 3.16	0.84
Workforce AI capability	5	3.32	0.78	3.24 to 3.39	0.84
Responsible AI climate	6	3.10	0.77	3.02 to 3.17	0.85
Perceived value	4	3.45	0.80	3.37 to 3.52	0.80
Responsible adoption	5	3.36	0.81	3.28 to 3.43	0.85

Scores range from 1 to 5, with higher values indicating greater readiness, capability, value, or adoption. CI, confidence interval.

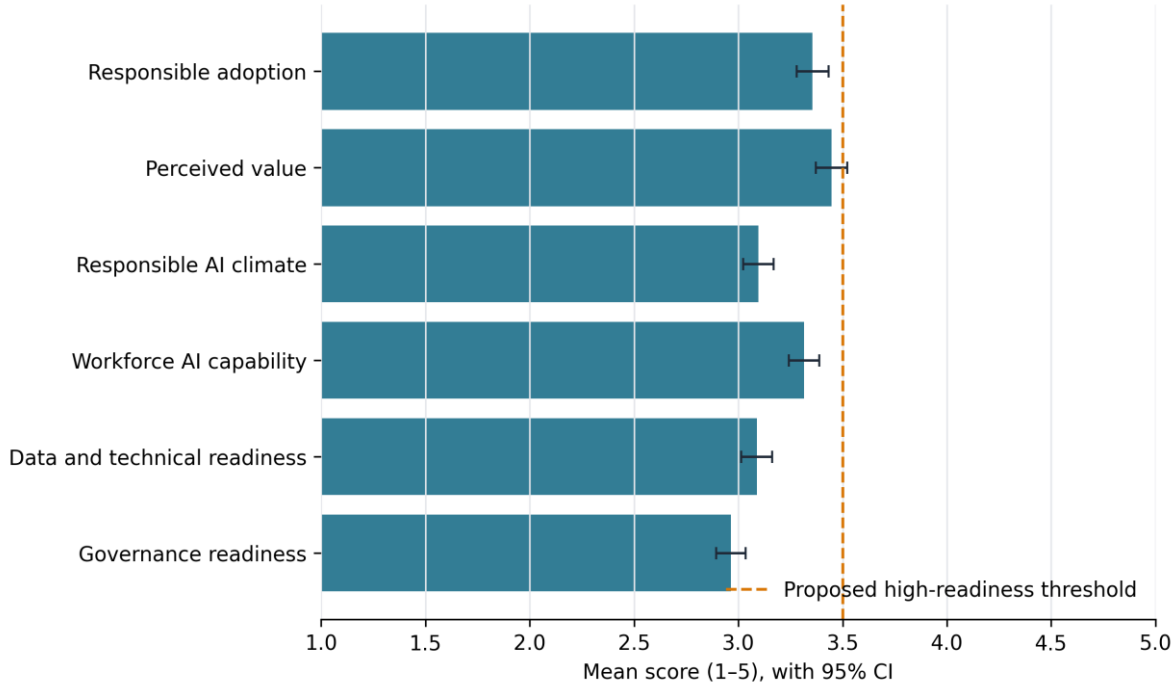


Figure 1: Mean Domain Scores With 95% Confidence Intervals. The Dashed Line Marks the Proposed High-Readiness Threshold Of 3.50.

3.3. Professional-Group Differences and High-Readiness Classification

Health information/informatics records had higher workforce AI capability than health administration records (3.46 vs 3.20; mean difference 0.26; Cohen d=0.33; p=0.001). They also had higher responsible adoption (3.45 vs 3.28; difference 0.17; d=0.21; p=0.031) and overall governance readiness (3.18 vs 3.07; difference 0.12; d=0.20; p=0.037). Differences in governance readiness, responsible AI climate, and perceived value were not statistically significant.

Overall, 119 of 432 (27.5%) synthetic records met the proposed high-governance-readiness threshold. The descriptive rate was 34.5% among records with formal AI training compared with 24.1% without training, and 33.3% among records with prior AI use compared with 22.5% without prior use. These unadjusted percentages are illustrative and should not be treated as intervention effects.

Table 3: Domain Scores by Professional Group.

Domain	HA mean (SD)	HI mean (SD)	Difference	Cohend	p value
Governance readiness	2.94 (0.80)	2.99 (0.69)	0.05	0.07	0.477
Data and technical readiness	3.03 (0.80)	3.16 (0.76)	0.14	0.17	0.074
Workforce AI capability	3.20 (0.73)	3.46 (0.81)	0.26	0.33	<0.001
Responsible AI climate	3.09 (0.75)	3.11 (0.79)	0.02	0.03	0.748
Perceived value	3.39 (0.84)	3.52 (0.73)	0.13	0.16	0.094

Responsible adoption	3.28 (0.83)	3.45 (0.78)	0.17	0.21	0.031
Overall governance readiness	3.06 (0.58)	3.18 (0.57)	0.12	0.20	0.037

Positive differences indicate higher scores in health information/informatics. P values are from Welch t tests.

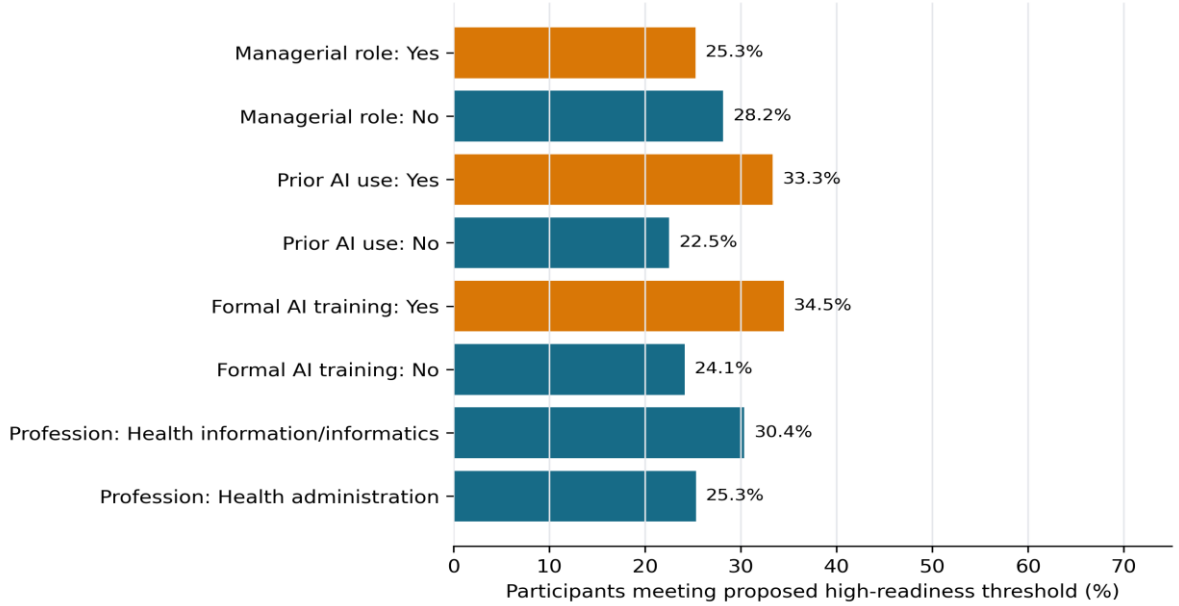


Figure 2: Percentage Meeting the Proposed High-Governance-Readiness Threshold Across Selected Groups.

3.4. Associations Among Constructs

All construct scores were positively correlated in the synthetic dataset. Responsible adoption correlated most strongly with responsible AI climate (Spearman rho=0.52) and workforce AI capability (rho=0.47). Governance readiness was strongly related to responsible AI climate (rho=0.52), consistent with the intended conceptual structure in which formal governance and day-to-day responsible practice reinforce one another.

Table 4: Spearman Correlations Among Simulated Construct Scores.

Construct	1	2	3	4	5	6
1. Governance readiness	1.00	0.43	0.32	0.52	0.20	0.41
2. Data and technical readiness	0.43	1.00	0.31	0.43	0.22	0.38
3. Workforce AI capability	0.32	0.31	1.00	0.41	0.28	0.47
4. Responsible AI climate	0.52	0.43	0.41	1.00	0.32	0.52
5. Perceived value	0.20	0.22	0.28	0.32	1.00	0.41
6. Responsible adoption	0.41	0.38	0.47	0.52	0.41	1.00

All coefficients are Spearman correlations. Statistical significance is not emphasized because the data-generating process intentionally imposed correlated domains.

3.5. Multivariable Model of Responsible Adoption

The adjusted model explained 44.7% of variance in responsible adoption (adjusted R2=0.425). The largest standardized construct coefficient was observed for responsible AI climate (B=0.204 per SD, 95% CI 0.124 to 0.283; p<0.001). Workforce capability, perceived value, governance readiness, and data and technical readiness were also independently associated with the outcome. Prior AI use remained positively associated after adjustment (B=0.159, 95% CI 0.026 to 0.292; p=0.019). Profession and formal training were no longer significant after inclusion of the construct scores, an illustrative pattern compatible with mediation through capability and organizational conditions.

Table 5: Multivariable Linear Regression for Simulated Responsible Adoption Score.

Predictor	B (robust SE)	95% CI	p value
Governance readiness (per 1 SD)	0.133 (0.039)	0.057 to 0.210	<0.01

Data and technical readiness (per 1 SD)	0.079 (0.034)	0.012 to 0.145	0.020
Workforce AI capability (per 1 SD)	0.167 (0.037)	0.096 to 0.239	<0.01
Responsible AI climate (per 1 SD)	0.204 (0.041)	0.124 to 0.283	<0.01
Perceived value (per 1 SD)	0.159 (0.036)	0.087 to 0.230	<0.01
Profession: health information/informatics	0.007 (0.066)	-0.123 to 0.137	0.916

Predictor	B (robust SE)	95% CI	p value
Formal AI training: yes	0.017 (0.071)	-0.123 to 0.158	0.811
Prior AI use: yes	0.159 (0.068)	0.026 to 0.292	0.019
Managerial role: yes	0.009 (0.077)	-0.143 to 0.160	0.910
Experience: 5–9 years (vs <5)	-0.078 (0.091)	-0.256 to 0.100	0.392
Experience: 10–14 years (vs <5)	-0.061 (0.088)	-0.234 to 0.112	0.487
Experience: ≥15 years (vs <5)	0.032 (0.083)	-0.131 to 0.196	0.698

Continuous construct predictors are standardized. Model includes center fixed effects, which are omitted for brevity. HC3 heteroskedasticity-robust standard errors. R2=0.447; adjusted R2=0.425.

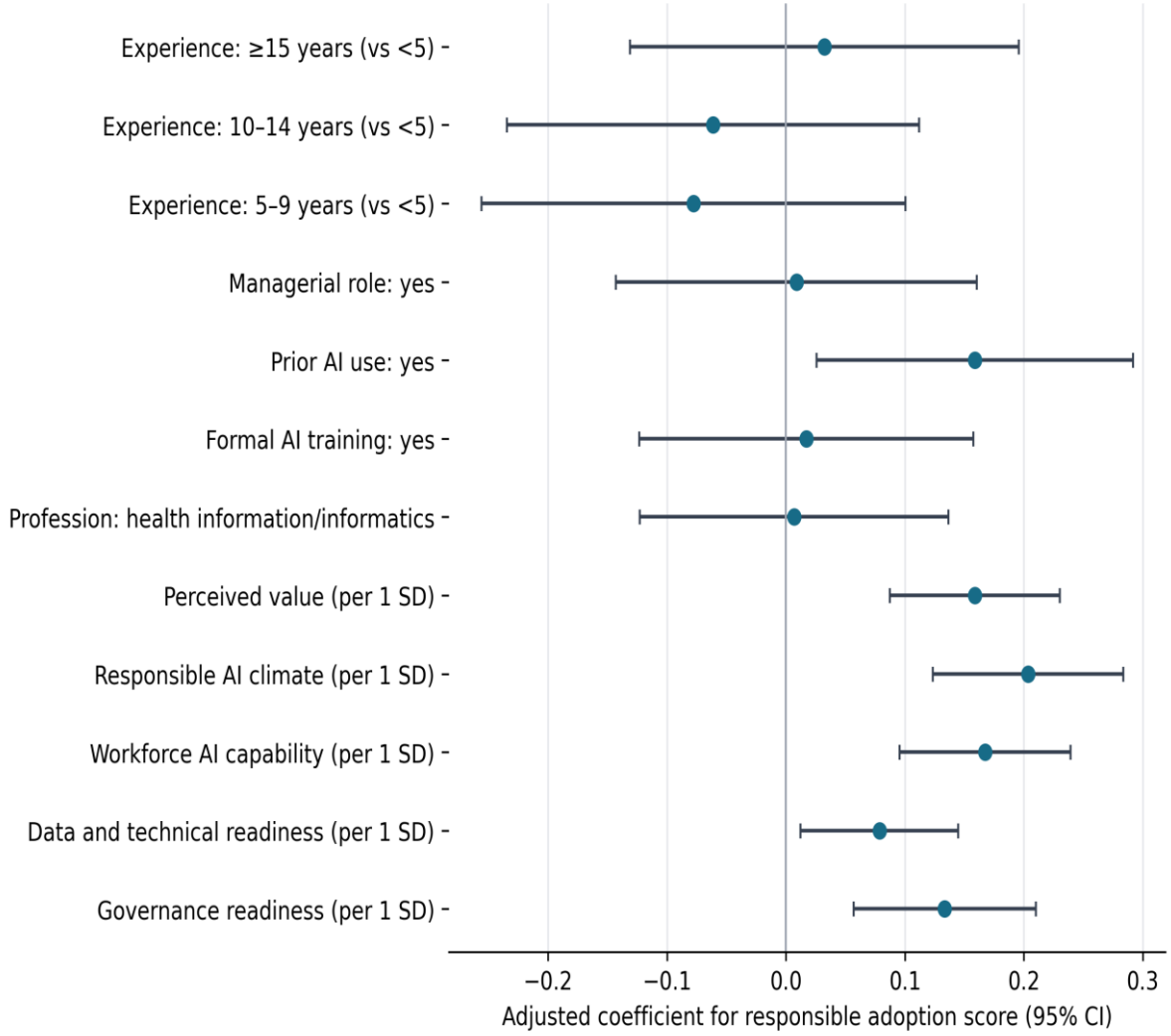


Figure 3: Adjusted Coefficients And 95% Confidence Intervals for Responsible Adoption. Center Fixed Effects Are Omitted.

4. DISCUSSION

4.1. Principal Findings

This methodological prototype demonstrates a feasible approach to assessing AI governance readiness among health administration and health information/informatics professionals. Its central simulated pattern is a readiness gap: respondents

may recognize the value of AI and express willingness to adopt approved tools while perceiving weaker written policy, oversight, risk classification, procurement assurance, and incident-reporting capacity. That gap is a useful hypothesis for the field study, not a conclusion about the participating workforce.

The adjusted model further illustrates that responsible adoption can be conceptualized as a sociotechnical outcome. It is associated not only with perceived value or individual familiarity, but also with responsible organizational climate, workforce capability, formal governance, and data and technical readiness. The loss of an independent professional-group or training effect after construct adjustment suggests a testable pathway in which occupation and education influence adoption through capability and organizational conditions. A future real-data study could examine this formally with mediation or structural equation modeling if measurement validity and sample size are adequate.

4.2. Relationship To Existing Evidence

The proposed interpretation is consistent with WHO guidance, which frames trustworthy AI as a governance and human-rights challenge rather than a purely technical achievement [1,2]. It also matches NIST's emphasis on continuous governance, risk mapping, measurement, and management [5]. In healthcare organizations, recent framework synthesis shows that principles alone are insufficient; assessment methods, lifecycle processes, and oversight structures must be operationalized [6].

The workforce focus is also supported by adoption literature. AI-capable organizations require local expertise, implementation capacity, performance monitoring, and the ability to intervene when systems fail [9]. Governance structures, trust, training, workflow compatibility, and legal or regulatory clarity recur as facilitators across studies [10]. Saudi survey evidence has linked stronger computer skills, AI knowledge, health informatics involvement, and technology experience with more favorable perceptions [12]. More recent studies describe a knowledge-enthusiasm gap in which professionals are positive about AI but less confident in their knowledge and institutional preparedness [17]. The proposed study extends this literature by making governance readiness, responsible climate, and administrative-information roles explicit.

4.3. Implications For Healthcare Organizations

If the field study reproduces a gap between perceived value and governance readiness, organizations should avoid treating enthusiasm as implementation readiness. A practical response would begin with an AI inventory, designated oversight body, risk-tiering process, approved-use policy, procurement and vendor-assurance criteria, privacy and cybersecurity review, local validation, monitoring plans, incident reporting, change control, and decommissioning criteria. These functions should connect to existing quality, safety, information governance, cybersecurity, procurement, legal, and clinical governance systems rather than operate as a disconnected AI committee.

Professional development should be role-specific. Health administrators may need training in risk ownership, procurement evidence, benefit realization, accountability, change management, and post-deployment oversight. Health information and informatics professionals may need deeper capability in data provenance, representativeness, interoperability, privacy engineering, model monitoring, drift, audit trails, and human-computer workflow design. Joint simulation exercises could help both groups practice evaluating an AI use case, escalating an incident, and deciding when deployment should be modified or suspended.

At the national and cluster level, common assessment tools could support benchmarking and shared learning. However, readiness scores should not become a compliance label without validation. Organizations need qualitative evidence, documentary review, and use-case-specific assurance in addition to staff perceptions. Alignment with Saudi data-protection and AI ethics requirements is essential, especially when AI tools process sensitive health data or transfer information across organizational or national boundaries [3,4].

4.4. Strengths And Limitations

The proposed study has several design strengths. It focuses on two professional groups with substantial but under-studied governance responsibilities; integrates international and Saudi frameworks; separates governance, technical, workforce, ethical-climate, value, and adoption domains; includes multiple centers; and specifies an auditable analysis with center adjustment and robust standard errors. The companion workbook preserves item-level data structure, scoring, code definitions, results, and figures.

The present prototype also has decisive limitations. First, every record is synthetic; therefore, sample characteristics, prevalence, reliability, correlations, p values, and regression coefficients have no empirical meaning. Second, the

questionnaire has not undergone expert content validation, translation testing, pilot administration, or factor analysis. Third, the proposed high-readiness threshold of 3.50 is arbitrary. Fourth, the eventual cross-sectional, self-report design will be vulnerable to selection bias, nonresponse, social desirability, common-method variance, and inability to infer causality. Fifth, professional categories and institution types may require broader representation. Finally, center fixed effects control average site differences but do not replace a carefully designed multilevel study when the number of centers and within-center samples are sufficient.

5. CONCLUSIONS

This model manuscript and analysis package provide a complete starting point for a multicenter study of AI governance readiness and responsible adoption among health administration and health information professionals. The synthetic analysis produces a coherent hypothesis: responsible adoption

may depend on the interaction of governance, data and technical infrastructure, workforce capability, responsible organizational climate, perceived value, and prior experience. The next valid step is not publication of these numbers; it is expert validation of the instrument, ethics approval, pilot testing, site recruitment, and collection of real multicenter data. Only then should the Results, Discussion, and conclusions be rewritten as empirical findings.

Declarations

Ethics Approval and Consent to Participate: Not applicable to the synthetic prototype because no human participants or identifiable data were used. Ethics approval, site permission, and informed consent are mandatory before the proposed field study.

Consent For Publication: Not applicable to the simulation. Any field-study requirements will be addressed in the approved protocol.

Availability Of Data and Materials: The synthetic item-level data, data-entry template, codebook, formula-based scoring, statistical results, and dashboard accompany this manuscript. They are provided for reproducibility and workflow testing only.

Competing Interests: None declared for this prototype; all authors must confirm before submission.

Funding: No funding is declared for the prototype; funding for the field study must be reported accurately.

Use of Generative Artificial Intelligence: Generative AI assisted with development of this methodological prototype, synthetic dataset, analysis workflow, and draft text. The named author and future coauthors are responsible for verifying the instrument, methods, references, statistical outputs, and final manuscript before field use or submission.

Status and Intended Use: This document combines a proposed field protocol with a fully worked synthetic analysis. It is designed to help the research team finalize the questionnaire, ethics application, data dictionary, sample plan, and statistical analysis before collecting data. The results section is deliberately written in journal style so that the analytical workflow can be inspected; however, all numerical results must be regenerated from real observations and independently verified before submission.

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