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ORGANISATIONAL READINESS, AI ADOPTION AND PROJECT PERFORMANCE IN GCC HEALTHCARE: A TOE-BASED STRUCTURAL MODEL AND MONTE CARLO POWER ANALYSIS

Specifying, and stress-testing the testability of, an integrated model of AI value in Gulf Cooperation Council healthcare projects

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Abstract : Healthcare organisations in the Gulf Cooperation Council (GCC) are adopting artificial intelligence (AI) to manage capacity, workforce and capital projects. Empirical research on whether this adoption improves resource use and project performance is still scarce, and it is typically based on isolated bivariate hypotheses and small samples. This paper makes two contributions. Theoretically, it develops an integrated structural model grounded in the Technology–Organisation–Environment (TOE) framework, organisational readiness theory and the Resource-Based View. In the model, technological readiness, organisational readiness and environmental support drive AI adoption intensity; implementation barriers weaken the readiness–adoption link; and adoption improves resource optimisation and project performance through staff attitude and trust and through decision-making efficiency. Twelve hypotheses are specified. Experimentally, the paper reports a Monte Carlo simulation (1,000 replications in each of 16 conditions) that tests whether the model can be tested under realistic GCC data conditions. The conditions cover eight sample sizes, two effect-size scenarios, Likert-type measurement and composite-based estimation. The simulation shows that the widely used inverse square root rule ($n \approx 275$ for paths of 0.15) materially overstates power once measurement error and correlated predictors are modelled. Paths of 0.15 reached only 0.63–0.67 power at $n = 275$ and needed about $n = 500$ for 0.80. The moderation hypothesis needed about $n = 750$, and composite estimates were attenuated by 4–26%. Based on these results, the paper recommends a minimum of 500 respondents, treating the moderation hypothesis as confirmatory only above 750, and a complete measurement and analysis protocol. The original doctoral design of 100–150 respondents would have had power of only 0.19–0.43 for the three smallest-effect hypotheses.

IndexTerms **- Artificial intelligence adoption, organisational readiness, TOE framework, healthcare project management, PLS-SEM, Monte Carlo simulation, statistical power, GCC.**

I. INTRODUCTION

Healthcare in the Gulf Cooperation Council (GCC) is being reshaped through large, state-sponsored transformation programmes in which AI features prominently. National strategies in Saudi Arabia and the United Arab Emirates identify healthcare as a priority sector for AI [1, 2], and hospitals across the region are deploying predictive capacity management, automated scheduling, operations centres and virtual-care platforms [3, 4, 5, 6]. Much of this change is delivered through projects. Project performance — on time, on budget and with the intended benefits — is therefore a direct determinant of whether transformation investments create value [7, 8].

Empirical research on AI in GCC healthcare management remains limited. A regional systematic review found the evidence base dominated by clinical prediction and diagnosis [9]. One of the few quantitative operational studies, from a Saudi health cluster with 287 respondents, found that an AI-driven operational management system was associated with higher perceived operational efficiency ($\beta = 0.525$), with staff attitude partially mediating the effect [10]. International implementation research consistently attributes AI success or failure to socio-technical conditions — data, interoperability, leadership, skills and regulation — rather than to algorithms alone [11, 12, 13].

Three weaknesses limit this literature. First, hypotheses are typically tested one at a time (AI → efficiency; barriers → adoption; readiness → adoption). This prevents the estimation of indirect and conditional effects and of the relative importance of drivers. Second, individual-level acceptance models such as TAM and UTAUT are frequently applied to what are organisational adoption decisions [14, 15]. Third — and least discussed — studies are often *underpowered*. Sample sizes of 100–200 recruited through

professional networks are common, and minimum-sample rules used in PLS-SEM research assume conditions, such as error-free measurement, that real survey data rarely meet [16]. An underpowered study of a complex model will fail to detect true small effects, which leads to incorrect conclusions that drivers such as environmental support "do not matter".

This paper responds with a theoretical and an experimental contribution. Theoretically, it consolidates five separately framed doctoral hypotheses into a single structural model with explicit mechanisms and a boundary condition. Experimentally, it reports a Monte Carlo simulation that determines, before any data are collected, what sample size is needed to test each hypothesis with adequate power under realistic measurement conditions [17]. The results are translated into a complete, submission-grade research protocol.

II. THEORETICAL FOUNDATIONS

2.1 Technology–Organisation–Environment framework

The TOE framework explains organisational adoption of technological innovations through three contexts. The technological context covers the characteristics of available technologies and their fit with existing systems. The organisational context covers structure, size, resources, managerial support and skills. The environmental context covers industry, regulation and government [18]. TOE has been validated widely for enterprise technologies and is preferred to individual-level models when the unit of adoption is the organisation [19]. In healthcare AI, each context maps directly onto barriers and enablers reported in implementation studies: data quality and interoperability (technological), leadership and skills (organisational), and regulation and national policy (environmental) [11, 12].

2.2 Organisational readiness and the Resource-Based View

Organisational readiness for change refers to members' shared commitment to a change and their perceived collective capability to implement it [20]. It sharpens the organisational context of TOE by distinguishing willingness from capacity, and it has a validated measure [21]. The Resource-Based View adds that technology produces competitive value only when combined with complementary organisational resources such as skills, processes and governance [22]. Reviews of AI and business value confirm that AI capability is a bundle of technical and human resources, and that value appears first at the process level and only later in performance [23]. This sequencing motivates the model's process-level mediators.

2.3 Human mediation and decision processes

AI outputs influence outcomes only when people act on them. Individual responses therefore matter — not as determinants of the organisational adoption decision, but as mechanisms through which adoption produces outcomes. Trust, explainability and staff involvement shape whether AI recommendations are used [24]. Regional evidence shows both favourable attitudes and substantial concern: in a survey of 1,026 Saudi healthcare providers, 76.2% considered AI useful, while 74.6% perceived privacy risks [25]. A second process mechanism is decision-making efficiency: AI consolidates dispersed data, produces forecasts and flags risks, which makes operational and project decisions faster and better informed [26, 27].

III. RESEARCH MODEL AND HYPOTHESES

3.1 Consolidating the doctoral hypotheses

The doctoral research from which this paper is derived framed five separate hypotheses: AI tools improve resource optimisation; AI improves project management efficiency; implementation challenges affect adoption; organisational readiness influences adoption; and AI-driven automation improves decision-making efficiency. Two of these address the same relationship from opposite directions, and none specifies how effects are transmitted. Table 1 shows how they are consolidated into one structural model (Figure 1).

Table 1: consolidation of the original doctoral hypotheses into the integrated model

Original doctoral hypothesis	Treatment in integrated model	Rationale
AI tools improve resource optimisation	H3, H5 and H9b (AIA → SA → RO)	Specifies the mechanism through which adoption affects resource outcomes
AI improves project management efficiency	Re-specified as project performance (PP): time, cost, scope, benefits; H6–H8	Aligns with multidimensional project-success literature
Implementation challenges affect adoption	H2: barriers moderate OR → AIA	Avoids duplicating readiness; explains when readiness converts into adoption
Organisational readiness influences adoption	H1a–H1c: TR, OR and ES as TOE antecedents	Separates technological, organisational and environmental readiness
AI automation improves decision-making efficiency	H4, H6 and H9a (AIA → DME → PP)	Positions decision quality and speed as a process mediator

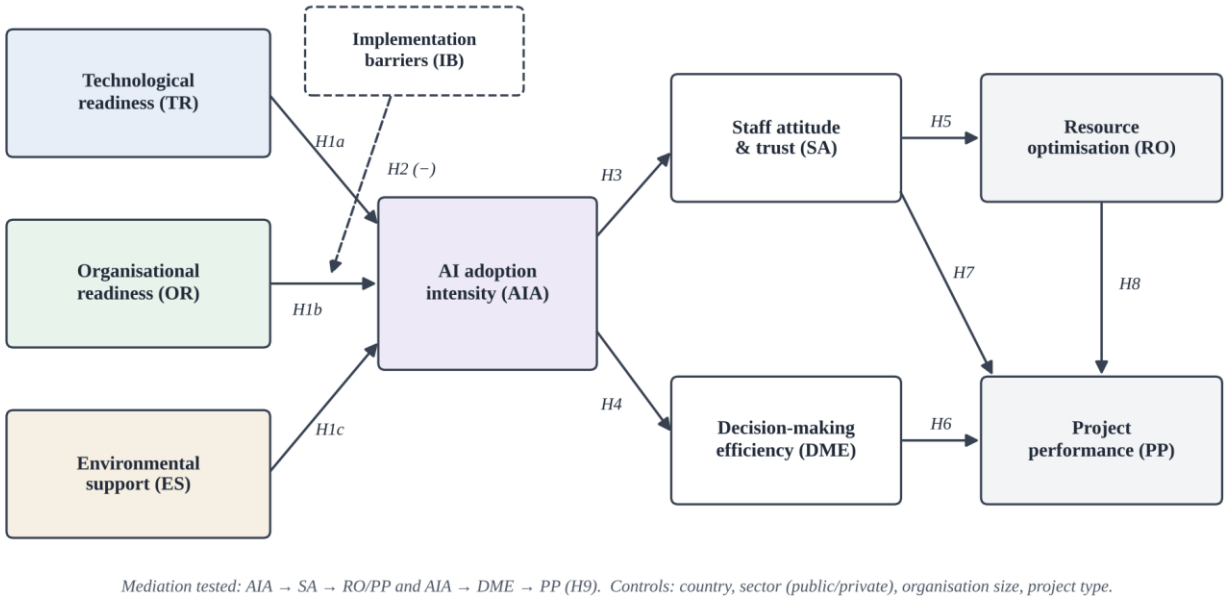

Figure 1: the integrated research model

3.2 TOE readiness and AI adoption intensity

AI adoption intensity (AIA) is defined as the breadth and depth of AI use across resource and project management functions: forecasting, scheduling, resource allocation, risk management and reporting. Technological readiness (TR) — integrated data platforms, adequate infrastructure and interoperability — is a precondition for AI, because models depend on timely, high-quality data and must integrate with operational systems [11, 28]. Organisational readiness (OR) — leadership commitment, workforce competence and an innovation-supportive culture — determines whether organisations commit resources and sustain change through implementation [20, 12]. Environmental support (ES) — national strategy, regulatory clarity and vendor ecosystems — is particularly salient in the GCC, where the state is regulator, funder and dominant provider [3].

- **H1a.** Technological readiness is positively associated with AI adoption intensity.
- **H1b.** Organisational readiness is positively associated with AI adoption intensity.
- **H1c.** Environmental support is positively associated with AI adoption intensity.

3.3 Implementation barriers as a boundary condition

Implementation barriers (IB) include resistance to change, data privacy concerns, integration costs and skills shortages. Barriers are usually modelled as a separate antecedent that mirrors readiness. Instead, this model proposes that barriers condition the *conversion* of readiness into use. Organisations that are committed and capable may still fail to adopt when barriers are high — a pattern seen in health technology projects that survive as pilots without reaching routine practice [29, 30]. Privacy-related barriers are especially salient in the GCC while new personal data protection regimes are being implemented [31, 32].

- **H2.** Implementation barriers negatively moderate the relationship between organisational readiness and AI adoption intensity, such that the relationship is weaker when barriers are high.

3.4 Mediating mechanisms and outcomes

Greater use of AI exposes staff to its benefits and limitations. Where tools are explainable and staff are involved, attitudes and trust improve, as the Saudi evidence of a strong AI → attitude path suggests [24, 10]. AI also accelerates and structures decisions [27, 26]. Positive staff attitude increases the likelihood that AI recommendations are acted upon, which improves resource optimisation (RO) and project performance (PP). Faster and better-informed decisions reduce delays, rework and scope drift, which improves project performance [33]. Better resource optimisation — fewer bottlenecks and better allocation of shared staff and facilities — in turn supports project delivery.

- **H3.** AI adoption intensity is positively associated with staff attitude and trust.
- **H4.** AI adoption intensity is positively associated with decision-making efficiency.
- **H5.** Staff attitude and trust are positively associated with resource optimisation.
- **H6.** Decision-making efficiency is positively associated with project performance.
- **H7.** Staff attitude and trust are positively associated with project performance.
- **H8.** Resource optimisation is positively associated with project performance.
- **H9a.** Decision-making efficiency mediates the relationship between AI adoption intensity and project performance.
- **H9b.** Staff attitude and trust mediate the relationship between AI adoption intensity and resource optimisation.

IV. Simulation Study: Method

4.1 Purpose

Before committing resources to data collection, a Monte Carlo study was conducted to answer one question: *what sample size is required to test each hypothesis in the model with at least 80% power, under data conditions realistic for GCC healthcare surveys?* Monte Carlo methods are the recommended approach to power analysis for structural models, because analytic formulae and rules of thumb cannot reflect model complexity, measurement error or the specific effect sizes hypothesised [17].

4.2 Data-generating model

Data were generated from a standardised latent structural model matching Figure 1. The four exogenous constructs (TR, OR, ES and IB) were drawn from a multivariate normal distribution with realistic intercorrelations. TR, OR and ES were intercorrelated at 0.25–0.30, and IB correlated negatively with them (−0.15 to −0.30). Endogenous constructs were generated from the hypothesised paths with residual variance set so that each latent variable had unit variance. Two effect-size scenarios were specified. The *expected* scenario uses path coefficients informed by prior evidence: the Saudi AI study reported paths of 0.53–0.59 for AI effects and 0.30 for staff attitude on efficiency [10]. Values were set more cautiously, at 0.40–0.45 for direct AI effects, 0.15–0.25 for readiness and outcome paths, and −0.12 for the interaction. The *conservative* scenario multiplies all paths by 0.7. Population values are shown in Table 2.

4.3 Measurement model

To reproduce real survey data, each construct was measured by four or five reflective indicators with loadings drawn uniformly from 0.70 to 0.85 — the range typically reported in published PLS-SEM studies. Continuous indicator values were discretised into seven-point Likert categories using fixed thresholds. Construct scores were computed as equally weighted composites of their indicators. This mirrors composite-based estimation as used in PLS-SEM [34].

4.4 Estimation and conditions

For each replication, every endogenous construct was regressed on its hypothesised predictors using ordinary least squares on standardised composites. Interaction H2 was estimated with the product of standardised OR and IB composites, following the two-stage logic used in PLS-SEM moderation analysis. Indirect effects (H9a, H9b) were tested with the joint-significance test, which requires both constituent paths to be significant and performs well in power and Type I error compared with alternatives [35]. Eight sample sizes (100, 150, 200, 275, 350, 500, 750 and 1,000) were crossed with the two scenarios, giving 16 conditions with 1,000 replications each (16,000 simulated datasets). Power was defined as the proportion of replications in which a hypothesis was supported at $\alpha = .05$, and attenuation as the percentage difference between the mean estimate and the population value. The simulation was implemented in Python (NumPy) with a fixed random seed for reproducibility; the code is available from the author on request.

V. Simulation Study: Results

5.1 Statistical power

Table 2 and Figure 2 report the results. In the expected scenario, the strong AI-to-mediator paths (H3, H4, H5) and the indirect effect via staff attitude (H9b) achieved power of at least 0.98 even at n = 100–150. The picture for smaller paths is very different. At n = 275 — the minimum implied by the inverse square root rule for a path of 0.15 [16] — power was only 0.67 for H1c (environmental support) and 0.63 for H7 (staff attitude → project performance). Both required about n = 500 to exceed 0.80. The moderation hypothesis H2 was the hardest to detect: power was 0.42 at n = 275 and 0.67 at n = 500, and 0.80 was exceeded only at n = 750. This is consistent with the well-documented difficulty of detecting interaction effects in field data [36].

Table 2: Monte Carlo power estimates by hypothesis and sample size (expected scenario) and minimum n for power ≥ 0.80

H	Path	True β	Mean est. (n=275)	n=150	n=275	n=350	n=500	n=750	Min n (expected)	Min n (conserv.)
H1a	TR → AIA	0.20	0.18	0.63	0.86	0.93	0.98	0.99	275	500
H1b	OR → AIA	0.25	0.22	0.78	0.95	0.99	0.99	1.00	200	350
H1c	ES → AIA	0.15	0.14	0.42	0.67	0.79	0.91	0.98	500	1,000
H2	OR × IB → AIA	-0.12	-0.09	0.23	0.42	0.48	0.67	0.84	750	> 1,000
H3	AIA → SA	0.45	0.39	1.00	1.00	1.00	1.00	1.00	100	150
H4	AIA → DME	0.40	0.34	0.99	1.00	1.00	1.00	1.00	100	150
H5	SA → RO	0.40	0.34	0.98	1.00	1.00	1.00	1.00	100	150
H6	DME → PP	0.25	0.22	0.80	0.96	0.98	0.99	0.99	150	350
H7	SA → PP	0.15	0.14	0.40	0.63	0.76	0.89	0.98	500	1,000
H8	RO → PP	0.20	0.18	0.56	0.83	0.89	0.98	0.99	275	500
H9a	AIA → DME → PP (indirect)	0.10	0.07	0.79	0.96	0.98	0.99	0.99	200	500
H9b	AIA → SA → RO (indirect)	0.18	0.13	0.98	1.00	1.00	1.00	1.00	100	200

Note: 1,000 replications per cell; $\alpha = .05$; seven-point Likert indicators with loadings 0.70–0.85; composite-based estimation. Indirect-effect "true β" is the product of the constituent paths. Power values are truncated to two decimals. Minimum n is the smallest simulated sample size at which power reached 0.80.

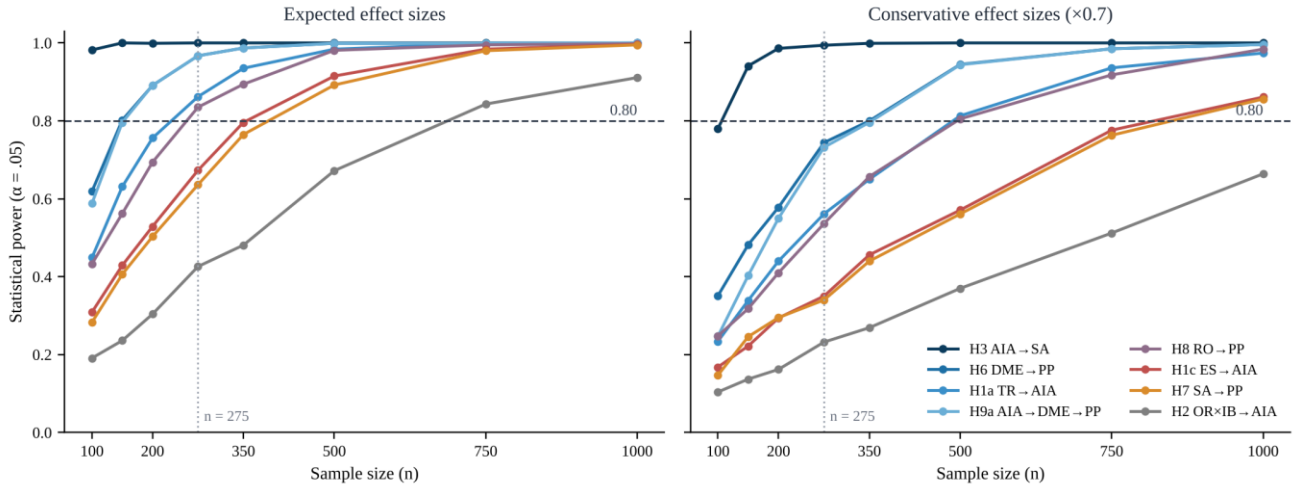

Figure 2: power curves for selected hypotheses under expected and conservative effect sizes

Under the conservative scenario, requirements rise sharply. Readiness paths H1a and H8 need about n = 500, H1c and H7 need about n = 1,000, and H2 does not reach 0.80 power within the simulated range (0.66 at n = 1,000). The original doctoral plan of 100–150 respondents would have had power of between 0.19 and 0.43 for H1c, H2 and H7 under expected effects, and between 0.10 and 0.24 under conservative effects. A null finding for these hypotheses would therefore have been uninformative.

5.2 Attenuation of estimates

Composite estimates were systematically smaller than the population values (Table 2). At n = 275, direct paths were attenuated by 4–15%, the interaction by 21%, and the indirect effects by 25–26%, because attenuation compounds across the two constituent paths. This has an important interpretive implication: indirect effects estimated from survey composites will understate the true role of mediating mechanisms. Researchers should therefore interpret modest indirect effects cautiously rather than dismissing them.

5.3 Why the rule of thumb fails

The inverse square root method assumes that the minimum path is estimated without measurement error and independently of other predictors [16]. In the simulated model, both assumptions fail. Measurement error from Likert indicators with loadings of 0.70–0.85 attenuates estimates, and correlated TOE predictors inflate standard errors in the adoption equation. These are not unusual features; they are the normal conditions of organisational survey research. The finding generalises beyond this model: for complex TOE-type structural models with correlated antecedents, minimum-sample rules should be supplemented by model-specific Monte Carlo analysis.

VI. Recommended Research Protocol

6.1 Design and sample

Based on the simulation, the following design is recommended. An explanatory sequential mixed-methods design will be used [37]: Phase 1 is a cross-sectional survey testing the structural model, and Phase 2 consists of semi-structured interviews that explain significant, non-significant and unexpected paths. The population comprises project managers, programme and PMO leads, operations and digital health managers, and senior clinicians with project responsibilities in public and private healthcare organisations across the six GCC states. A **minimum of 500 usable responses** is recommended, which gives at least 0.89 power for every main-effect hypothesis under expected effects. H2 should be pre-registered as *exploratory* unless at least 750 responses are achieved. Stratified purposive sampling with quotas by country and sector is recommended, using health authorities, professional associations and hospital PMOs as distribution channels to reach the required numbers. Non-response bias should be assessed by comparing early and late respondents.

6.2 Measurement instrument

All constructs are measured reflectively on seven-point scales, adapting established instruments where available (Table 3; sample items in Appendix Table A1). The instrument will be prepared in English and Arabic using forward and back-translation [38], reviewed by a panel of three to five academic and practitioner experts for content validity, and piloted with about 30 respondents. Control variables are country, sector, organisation size and project type. Because the simulation shows that perception-based outcomes dominate the literature, objective indicators — schedule variance, cost variance and bed occupancy — should be collected for a sub-sample of organisations to triangulate self-reported performance.

Table 3: constructs, operational definitions and item sources

Construct	Operational definition	Items	Basis for items
Technological readiness (TR)	Availability and integration of data, infrastructure and interoperable systems needed for AI	4	TOE literature [19]; implementation barriers [11]
Organisational readiness (OR)	Leadership commitment, workforce competence and culture supporting AI-enabled change	5	ORIC [21]; readiness theory [20]
Environmental support (ES)	Regulatory clarity, national policy support and vendor/partner ecosystem for AI	4	TOE environmental context [18, 3]
Implementation barriers (IB)	Perceived resistance, privacy concerns, integration costs and skills gaps	4	Barrier taxonomies [12, 11]

Construct	Operational definition	Items	Basis for items
AI adoption intensity (AIA)	Breadth and depth of AI use across forecasting, scheduling, allocation, risk and reporting	5	Developed for this study from AI-in-PM literature [27, 39]
Staff attitude and trust (SA)	Favourable evaluation of, and willingness to rely on, AI outputs	5	Adapted from [10, 24]
Decision-making efficiency (DME)	Speed, timeliness and information quality of project decisions	4	Adapted from AI decision-support literature [26]
Resource optimisation (RO)	Effectiveness of allocation and utilisation of staff, beds, equipment and budget	5	Adapted from operational efficiency scale [10]
Project performance (PP)	Achievement of schedule, budget, scope/quality and intended benefits	5	Project success dimensions [40, 7]

6.3 Analysis plan

Partial least squares structural equation modelling (PLS-SEM) is appropriate because the model is complex, includes mediation and moderation, and has predictive as well as explanatory aims [34]. Table 4 sets out the procedures and acceptance criteria. Mediation is tested with bootstrapped indirect effects [41], moderation with the two-stage approach, and out-of-sample predictive power with PLSpredict [42].

Table 4: analysis procedures and acceptance criteria

Stage	Test	Criterion
Measurement model	Indicator reliability	Outer loadings ≥ 0.708
	Internal consistency	Cronbach's α and composite reliability 0.70–0.95
	Convergent validity	Average variance extracted (AVE) ≥ 0.50
	Discriminant validity	HTMT < 0.85 (conservative) or < 0.90 [43]
Common method bias	Procedural and statistical remedies	Anonymity, separated scales, varied anchors [44]; full-collinearity VIF < 3.3 [45]
Structural model	Collinearity	Inner VIF < 3
	Path significance	Bootstrapping with 10,000 subsamples; 95% bias-corrected confidence intervals
	Explanatory power	R^2 (0.25 weak, 0.50 moderate, 0.75 substantial); f^2 effect sizes
	Predictive power	Q^2predict > 0; PLSpredict comparison with linear benchmark
Mediation and moderation	Indirect effects; interaction term	Significant bootstrapped indirect effect; two-stage interaction with simple-slope plot
Robustness	Heterogeneity and sensitivity	Multi-group analysis by country and sector; sensitivity to objective-outcome sub-sample

6.4 Qualitative phase and ethics

Twelve to fifteen participants, selected purposively from survey respondents who agree to follow-up and spanning countries, sectors and adoption levels, will be interviewed. The interview guide will be built around the survey results — for example, why a hypothesised path was not supported, or how barriers prevented ready organisations from adopting AI. Transcripts will be analysed thematically [46] and integrated with the quantitative results in a joint display. Ethical approval will be obtained from the university ethics committee and, where required, from participating health authorities. Participation is voluntary and anonymous, no patient data are collected, and data are reported only in aggregate.

VII. DISCUSSION

7.1 Theoretical contributions

The paper makes three theoretical contributions. First, it moves research on AI in healthcare management from bivariate testing to an integrated structural explanation in which direct, indirect and conditional effects are estimated together. Second, it resolves a level-of-analysis problem by placing organisational TOE readiness upstream of adoption and individual acceptance downstream as a mediating mechanism. Third, it reconceptualises implementation barriers as a boundary condition on readiness rather than as a mirror-image predictor. This offers a testable explanation for the familiar pattern of technically ready organisations whose AI projects stall [29].

7.2 Methodological contributions

The simulation contributes new evidence on the *testability* of TOE-type models. It shows that a widely used minimum-sample rule overstates power for small paths under realistic measurement, that interaction hypotheses in such models require samples of 750 or more, and that indirect effects estimated from composites are attenuated by about a quarter. These findings matter beyond this study. Several published TOE and AI-adoption studies with samples of 150–300 may have reported non-significant environmental or interaction effects that reflect low power rather than true absence. The recommended practice is to run a model-specific Monte Carlo analysis at the design stage and to report it alongside the hypotheses.

7.3 Practical contributions

For GCC health authorities and hospital executives, the validated model will indicate which readiness investments — data infrastructure, leadership and skills, or regulatory clarity — produce the greatest gains in adoption, and whether AI value depends more on staff trust or on decision efficiency. For research funders and doctoral supervisors in the region, the simulation offers a concrete warning: small-sample studies of complex AI-adoption models are likely to produce false negatives, so funding and supervision should be calibrated to the sample sizes the model actually requires.

7.4 Limitations and future research

The simulation approximates PLS-SEM with equally weighted composites; PLS weighting typically produces slightly higher reliability, so the power estimates are mildly conservative. Population values were set from limited prior evidence; researchers with better priors should re-run the simulation, and the code is available for this purpose. The planned survey is cross-sectional and largely self-reported, which limits causal inference; longitudinal and objective-outcome designs are recommended. Finally, the model does not distinguish between AI technologies — for example, predictive analytics and generative AI — and future studies could treat technology type as a moderator.

VIII. Conclusion

AI is increasingly central to how GCC healthcare organisations plan resources and deliver projects, but the field lacks integrated and adequately powered empirical models. This paper has proposed a TOE-based structural model in which readiness drives AI adoption, barriers condition that relationship, and staff attitude and decision-making efficiency transmit adoption into resource optimisation and project performance. A Monte Carlo simulation of 16,000 datasets shows that testing the model credibly requires at least 500 respondents, and about 750 for the moderation hypothesis — far more than is common in the regional literature. The model, the simulation evidence and the accompanying protocol provide a rigorous and replicable basis for multi-country empirical research in the region.

IX. Declarations

Conflict of interest: The author declares no conflict of interest. **Funding:** This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors. **Data and code availability:** Simulation code and output are available from the author on request. **Ethics:** Not applicable to the simulation study; the planned survey will require ethical approval as described in Section 6.4.

X. Appendix

Table A1: illustrative survey items (seven-point agreement scale)

Construct	Sample items
Technological readiness	Our organisation's clinical and operational data are accurate and complete enough to support AI tools. Our information systems can exchange data with AI applications without major manual work.
Organisational readiness	Senior leadership actively sponsors the use of AI in our projects. Our project teams have the skills required to use AI tools effectively.
Environmental support	National and regulatory guidance on the use of AI in healthcare is clear. Government initiatives encourage our organisation to adopt AI.
Implementation barriers	Staff resistance slows the introduction of AI tools in our projects. Data privacy requirements make it difficult to deploy AI tools.
AI adoption intensity	We use AI tools to forecast demand or resource needs for our projects. We use AI tools to identify and monitor project risks.
Staff attitude and trust	I trust the recommendations produced by the AI tools we use. AI tools make my work on projects easier.
Decision-making efficiency	AI tools enable project decisions to be made more quickly. AI tools improve the quality of information available for project decisions.
Resource optimisation	AI tools help us allocate staff to where they are most needed. AI tools reduce idle capacity or waste in our resources.
Project performance	Our AI-supported projects are completed on schedule. Our AI-supported projects deliver their intended benefits.

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