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ARTIFICIAL INTELLIGENCE FOR RESOURCE OPTIMISATION AND PROJECT MANAGEMENT IN GCC HEALTHCARE: AN INTEGRATIVE REVIEW, EVIDENCE-MATURITY APPRAISAL AND THE TOE-HM FRAMEWORK

Theorising when and how AI creates operational and project value in Gulf Cooperation Council health systems

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Abstract : Gulf Cooperation Council (GCC) governments are investing heavily in artificial intelligence (AI) to make healthcare delivery more efficient, yet the evidence that AI improves the use of operational resources and the management of healthcare projects has not been systematically appraised. This paper makes three original contributions. First, it reports an integrative review of 26 sources on AI in healthcare operations, implementation and project management, coded by domain, region and design. Second, it introduces a six-level Evidence-Maturity Ladder (L0 announcement to L5 comparative outcome evaluation) and applies it to the 12 primary sources in the corpus. GCC evidence peaks at L3 (model development and validation), half of the GCC primary sources sit at L2 (perception surveys), and no source anywhere in the corpus reaches L5. Third, it develops the TOE-HM framework (Technology–Organisation–Environment with Human Mediation), which explains AI value as the product of three readiness conditions, a barrier-conditioned conversion of readiness into adoption, and two human mediating mechanisms — staff attitude and trust, and decision-making efficiency. Six propositions and three GCC-specific boundary conditions are specified. The analysis shows that the dominant constraint on AI value in the region is not algorithmic capability but the absence of outcome-grade evidence and of the organisational conditions that convert adoption into measurable resource and project gains. A prioritised research agenda is proposed.

IndexTerms **- Artificial intelligence, healthcare operations, resource optimisation, healthcare project management, GCC, TOE framework, evidence maturity, integrative review.**

I. INTRODUCTION

Healthcare systems in the six Gulf Cooperation Council (GCC) states — Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates — operate under a distinctive set of pressures. Demand is rising with the prevalence of chronic and lifestyle-related disease and with population growth; clinical workforces depend heavily on expatriate professionals; and per-capita operating costs are high by international standards. Governments have responded with ambitious transformation programmes. Saudi Vision 2030 and its Health Sector Transformation Program, and the UAE National Strategy for Artificial Intelligence 2031, explicitly position AI as a lever for both better care and more efficient use of scarce resources [1, 2, 3]. Visible flagship initiatives include the UAE Ministry of Health and Prevention's AI-enabled operations centre for patient flow and the Saudi SEHA Virtual Hospital, which was launched with a network of 130 connected hospitals [4, 5].

Much of this change is delivered through projects: digital hospital builds, electronic medical record (EMR) consolidations, command centres and AI pilots. Whether AI improves how resources are used, and whether it improves how such projects are managed, are therefore questions of considerable economic and policy significance. The academic literature has not kept pace. Reviews of AI in healthcare remain dominated by clinical applications such as imaging, diagnosis and risk prediction [6, 7]. A systematic review of AI in Middle Eastern health systems synthesised 100 studies; its dominant themes concerned the prediction of disease, diagnosis and outcomes, while the prediction of organisational issues formed a separate and narrower theme [8]. Meanwhile,

international experience warns that ambitious healthcare AI and ICT programmes frequently over-promise, stall at pilot stage, or survive as projects without ever entering routine practice [9, 10].

Two gaps follow. The first is *empirical*: there is no appraisal of how strong the evidence for AI's operational and project value actually is, particularly in the GCC. Counting studies is not enough; what matters is whether the evidence has progressed from announcements and perceptions to measured outcomes. The second is *theoretical*: existing studies typically borrow individual-level acceptance models such as the Technology Acceptance Model (TAM) to explain what are organisational adoption decisions [11, 12], and they rarely specify the mechanisms through which adoption produces resource and project outcomes.

This paper addresses both gaps through three research questions:

- **RQ1.** What is the composition of the evidence on AI for resource optimisation and project management in healthcare, by domain, region and design?
- **RQ2.** How mature is that evidence, and how does GCC evidence compare with evidence from elsewhere?
- **RQ3.** What theoretical framework best explains the conditions and mechanisms through which AI creates resource and project value in GCC healthcare?

The paper's contributions are threefold. It provides a transparent, coded appraisal of the evidence base (RQ1). It introduces and applies a new Evidence-Maturity Ladder that distinguishes six levels of evidence for organisational AI value (RQ2). And it develops the TOE-HM framework, an extension of the Technology–Organisation–Environment model that adds a barrier-conditioned conversion mechanism and two human mediators, with formal propositions and region-specific boundary conditions (RQ3).

II. Conceptual Background

2.1 Resource optimisation in healthcare

In this paper, *resource optimisation* refers to aligning capacity — staff, beds, theatres, equipment, consumables and budgets — with demand, so that waste, idle capacity and bottlenecks are minimised without compromising quality or safety. Operational AI applications relevant to this goal include demand and admission forecasting, length-of-stay prediction, rostering and scheduling optimisation, patient-flow management in command centres, supply-chain and inventory optimisation, and the automation of administrative work such as documentation and coding [13, 14, 15]. These applications differ from clinical AI in an important respect: their value is realised only when managers change allocation decisions, so their benefits depend on organisational processes as much as on predictive accuracy.

2.2 Healthcare project management and project success

Healthcare project management refers to the planning, execution and control of time-bound change initiatives such as facility commissioning, system implementations and service redesigns. Project success is multidimensional. Beyond the "iron triangle" of cost, time and quality, it includes benefits to the organisation, its users and its future capability [16, 17]. Classical research identified critical success factors such as top-management support, a clear mission, stakeholder consultation and monitoring and feedback [18]. In public-sector digital transformation, disciplined project management strongly conditions whether technology investments deliver their intended value [19]. AI is relevant to project management in two ways: as the *object* of projects (AI implementations are themselves projects), and as a *tool* for managing projects through estimation, scheduling, risk prediction and portfolio selection [20].

2.3 Theoretical lenses on organisational AI adoption

Individual-level models such as TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) explain user acceptance through perceived usefulness, ease of use and social influence [11, 12]. Diffusion of Innovations theory explains how innovations spread through social systems [21]. These models are valuable but insufficient for questions of organisational value, because decisions to deploy AI for resource and project management are made by organisations, constrained by infrastructure and regulation, and realised through organisational routines.

The Technology–Organisation–Environment (TOE) framework addresses this by explaining firm-level adoption through three contexts: the *technological* (available technologies and their fit with existing systems), the *organisational* (structure, resources, managerial support and skills) and the *environmental* (industry, regulation and government) [22, 23]. The Resource-Based View complements TOE by explaining why similar AI investments produce different results: value depends on how technology is combined with complementary human and organisational resources [24, 25]. Healthcare implementation frameworks — the Consolidated Framework for Implementation Research (CFIR) and the NASSS framework for non-adoption, abandonment, scale-up, spread and sustainability — reinforce the point that technology outcomes emerge from interactions among the technology, the adopting organisation, its people and the wider system [26, 27]. Finally, organisational readiness for change theory distinguishes members' commitment to change from their perceived capability to implement it [28].

2.4 The GCC context

Three features of the GCC context matter for theory. First, the state is simultaneously the principal healthcare funder, the dominant provider and the regulator, so environmental pressure for AI adoption is unusually strong and top-down [3]. Second, the regulatory environment for health data is developing rapidly; Saudi Arabia's Personal Data Protection Law and the UAE's Federal Decree-Law No. 45 of 2021 create new obligations for data use in AI systems [29, 30]. Third, workforce composition is distinctive: a large expatriate workforce with relatively high mobility affects the retention of implementation know-how. These features suggest that models developed in Europe or North America may require region-specific boundary conditions.

III. Method

3.1 Design

An integrative review design was chosen because the relevant evidence is heterogeneous — quantitative and qualitative empirical studies, case analyses, systematic and scoping reviews, conceptual papers, protocols and policy announcements — and because the aim is conceptual synthesis and theory development rather than effect-size estimation [31, 32]. Integrative reviews are particularly suited to emerging topics in which the evidence base is fragmented and theory is underdeveloped.

3.2 Search and identification

The corpus was assembled in two stages. First, the literature reviewed in the author's doctoral research on AI in GCC healthcare project management was screened for relevance. Second, targeted searches were conducted in PubMed, Google Scholar and publisher platforms, and in GCC government and news sources for policy initiatives, using combinations of the terms "artificial intelligence", "machine learning", "hospital management", "operational efficiency", "length of stay", "patient flow", "resource allocation", "project management", "readiness", "perception" and the names of the six GCC states and "Middle East". Reference lists of included reviews were hand-searched.

3.3 Eligibility

Sources were included if they (a) were peer-reviewed journal articles, peer-reviewed conference papers, book chapters, or official government or reputable press reports of named initiatives; (b) were published between 2005 and 2025; and (c) addressed AI, or closely related digital health technology, in operational, managerial, project or implementation contexts in healthcare, or provided seminal clinical-AI evidence relevant to adoption and value. Purely technical algorithm papers and clinical accuracy studies with no organisational dimension were excluded. General management and information systems sources outside healthcare were used for theory building but were not included in the coded corpus. The final coded corpus comprised 26 sources.

3.4 Coding scheme

Each source was coded on four dimensions. *Primary domain*: operations (resource and capacity management), project management, adoption and implementation, clinical, or policy and governance. *Region*: GCC, wider Middle East and North Africa (MENA), or international. *Design*: quantitative empirical, qualitative/mixed/case, review, conceptual/policy (including protocols and frameworks), or grey literature/announcement. *Evidence maturity* (primary sources only): the level on the Evidence-Maturity Ladder defined in Table 1. The ladder is an original instrument developed for this review. It adapts the logic of evidence hierarchies to organisational AI, where the critical question is not whether a model is accurate but whether its use changes operational outcomes.

Table 1: the Evidence-Maturity Ladder for organisational AI value

Level	Label	Definition and typical evidence
L0	Announcement / claim	Public statement of deployment or expected benefits without reported data (press releases, launch reports)
L1	Concept / protocol	Conceptual model, framework or published evaluation protocol; no outcome data yet
L2	Perception / readiness	Survey or interview evidence on attitudes, readiness, perceived efficiency or perceived barriers
L3	Model development and validation	Predictive or optimisation model built and validated on retrospective data; or model-based projection of benefits
L4	Deployment case evidence	Real-world deployment described with qualitative or descriptive outcome evidence, including documented failures
L5	Comparative outcome evaluation	Measured operational or project outcomes compared against a control, baseline or counterfactual (e.g. controlled before–after, stepped-wedge, trial)

3.5 Analysis and rigour

Coded data were tabulated to answer RQ1 and RQ2 (Appendix Table A1 lists every source and its codes). For RQ3, sources were read in full and analysed thematically using a reflexive approach [33]; barriers and enablers were then mapped deductively onto the TOE contexts, and mechanism statements (claims about *how* AI affects outcomes) were extracted to inform theory building. To support transparency, the coding rules are specified in Section 3.4 and the full coding is reported so that other researchers can audit or replicate it. Coding was conducted by the author; independent double-coding with inter-rater agreement is recommended in any extension of this work.

IV. RESULTS

4.1 Composition of the evidence base (RQ1)

Of the 26 sources, nine (35%) concern the GCC, one concerns the wider Middle East, and sixteen (62%) are international. By domain, operations is the largest category (11 sources), followed by adoption and implementation (6), clinical (5), project management (2) and policy and governance (2). Figure 1 cross-tabulates domain and design. Two patterns are notable. First, reviews and conceptual papers together account for 16 of the 26 sources (62%), against only five quantitative empirical studies; the field is still more often summarised than studied. Second, project management is the thinnest domain: only two sources address AI or digital technology in the management of healthcare projects, one conceptual [20] and one a qualitative case of an ICT innovation project that survived as a project without reaching routine use [10].

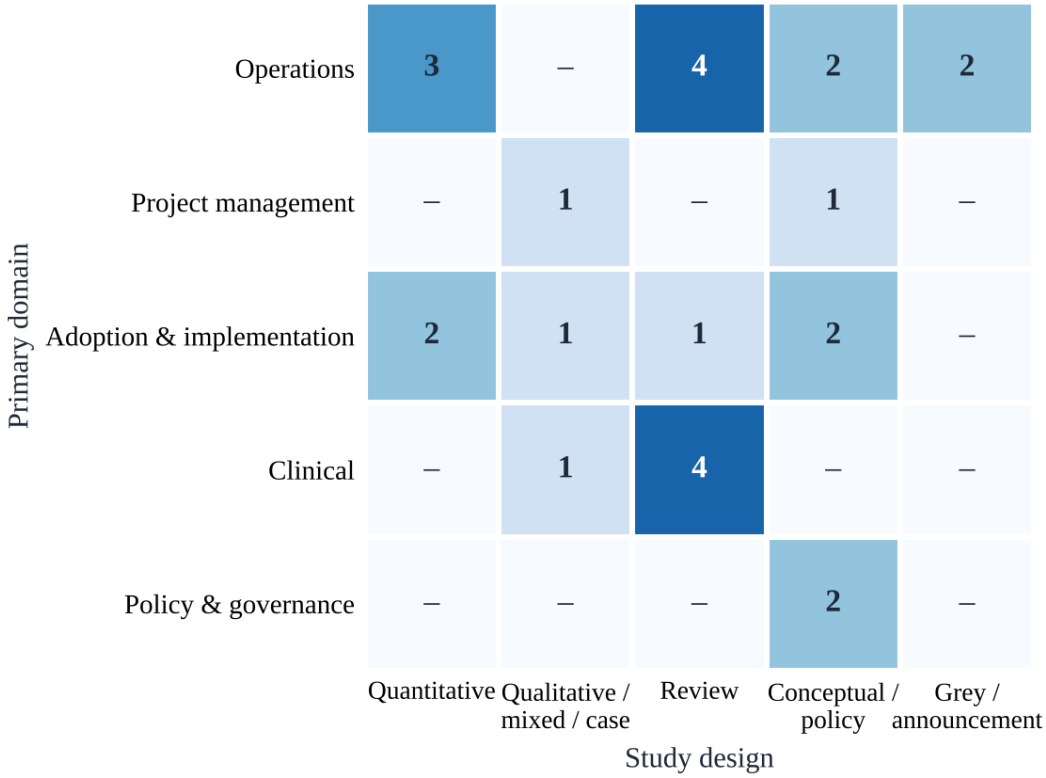

Figure 1: composition of the coded corpus by primary domain and study design (n = 26)

4.2 Evidence maturity (RQ2)

Twelve of the 26 sources are primary sources that can be placed on the Evidence-Maturity Ladder (Figure 2). GCC primary evidence clusters at the lower levels. Two GCC sources are L0 announcements of major AI-enabled operational initiatives that report no outcome data [4, 5]. Three are L2 studies of perception or perceived efficiency. A national survey of 1,026 Saudi healthcare providers found that 76.2% considered AI useful in their field, while 74.6% saw at least some risk of serious privacy problems and 73.3% were at least mildly worried about being replaced [34]. A survey of 374 radiology professionals in Saudi Arabia found that 58.6% reported limited AI knowledge and inadequate training [35]. The strongest GCC study of operational value — a PLS-SEM analysis of 287 staff in a Saudi health cluster — found that an AI-driven operational management system was positively associated with operational efficiency ($\beta = 0.525$) and with staff attitude ($\beta = 0.592$), with staff attitude partially mediating the effect [36]. However, efficiency was self-reported, which places the study at L2. The highest-level GCC source is an L3 study from a tertiary hospital in Riyadh, which developed and validated machine-learning ensembles to predict length of stay for 4,930 cardiac inpatient encounters, a capability directly relevant to bed and capacity planning [37]. The study reports predictive accuracy, not changes in bed utilisation after deployment.

Non-GCC primary sources reach L4: documented deployment cases, notably the IBM Watson oncology experience and a Norwegian health ICT project [9, 10]. Both are, instructively, accounts of value that failed to materialise. An AI command-centre evaluation protocol in acute care in England is designed to produce L5 evidence but is itself at L1 [38]. **No source in the corpus reaches L5.** In other words, within this corpus there is no comparative evidence that AI deployment improved measured operational or project outcomes in healthcare, either in the GCC or elsewhere.

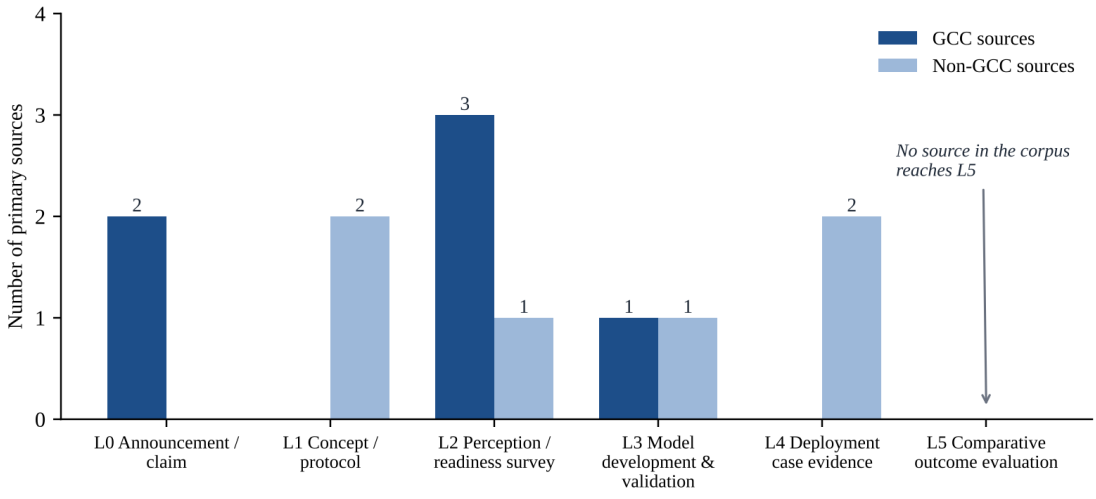

Figure 2: distribution of primary sources on the Evidence-Maturity Ladder, GCC versus non-GCC (n = 12)

4.3 Theme 1: where AI creates resource value

Across the corpus, the most consistent claims and evidence for resource value concern three operational domains. The first is *demand forecasting and capacity management*: predictive models of admissions, arrivals and length of stay support the planning of beds, rosters and theatre time [14, 15, 37]. The second is *patient flow and command-centre operations*, where real-time data integration lets managers anticipate bottlenecks. The UAE's operations centre and evaluation work on AI command centres in England illustrate both the ambition and the absence of outcome evidence [4, 38]. The third is *administrative automation*, including scheduling, documentation, coding and inventory management, which releases staff time [13, 39, 40]. Earlier modelling of EMR systems is a cautionary benchmark: projected savings were large, but they depended on interoperability and process redesign that many implementations did not achieve [41].

4.4 Theme 2: AI in the management of healthcare projects

Evidence for AI in the planning and control of healthcare projects — as distinct from routine operations — is the least developed strand. Contributions are conceptual: AI-supported knowledge management for adaptive planning is proposed to reduce planning errors in complex, interdisciplinary healthcare projects [20]. No source measured the effect of AI tools on objective project outcomes such as schedule variance, cost variance, scope stability or benefits realisation. This absence matters because it is precisely in GCC capital and transformation projects that the largest sums are committed.

4.5 Theme 3: human mediation of AI value

AI changes outcomes only when people trust and act on its outputs. The Saudi evidence shows staff attitude transmitting part of the effect of AI on efficiency [36]. Explainability is a precondition for trust in high-stakes settings [42], and excluding frontline staff from design is a recurrent cause of non-adoption [43]. Regional surveys suggest that favourable attitudes coexist with substantial concerns about privacy, job security and skills [34, 35], which implies that attitude is a variable to be managed rather than a background condition. The second mechanism is *decision-making efficiency*: AI consolidates data, generates forecasts and flags risks, which can make managerial decisions faster and better informed [14, 20].

4.6 Theme 4: barriers and enablers through the TOE lens

Table 2 maps the barriers and enablers reported across the corpus onto the three TOE contexts. Barriers are overwhelmingly socio-technical rather than algorithmic. Poor data quality, fragmented legacy systems and limited interoperability recur in every type of study [43, 44]. Organisational factors — leadership sponsorship, digital skills, change readiness and the ability to move beyond pilots — determine whether technically sound tools reach routine use [10, 28]. The environmental context of the GCC is distinctive: strong state sponsorship and national AI strategies create momentum, while new data protection laws create compliance obligations and reliance on international vendors raises questions of ownership and capability transfer [3, 29, 30].

Table 2: barriers and enablers of AI for resource and project management mapped to the TOE framework

TOE context	Barriers reported	Enablers reported
Technological	Poor data quality and completeness; legacy and fragmented systems; limited interoperability; opaque "black-box" models; integration cost	Integrated EMR and data platforms; standards-based interoperability; explainable models; structured AI product-development pathways [45]
Organisational	Weak leadership sponsorship; low digital and data skills; resistance to change; exclusion of end users from design; projects that survive as pilots without scale-up	Executive sponsorship; workforce upskilling; clinician and manager co-design; dedicated implementation teams; disciplined project and benefits management
Environmental	Regulatory uncertainty about AI accountability; data protection and localisation requirements; vendor dependence; workforce mobility	National AI strategies and funding; emerging regulatory frameworks; public–private partnerships; regional centres of excellence

4.7 Theme 5: the evidence gap

Together, the results reveal a structural gap between investment and evidence. GCC governments have made large, visible commitments to operational AI, but the published evidence of operational value is concentrated at L0–L3 and relies heavily on perceived rather than measured outcomes. Evidence is also concentrated geographically: all GCC empirical sources in the corpus come from Saudi Arabia, with policy initiatives from Saudi Arabia and the UAE, and none from Bahrain, Kuwait, Oman or Qatar. Finally, theory is rarely explicit; several studies are atheoretical or apply individual acceptance models to organisational questions, which limits cumulative knowledge [46, 47].

V. THEORY DEVELOPMENT: THE TOE-HM FRAMEWORK

5.1 Rationale

The results suggest that existing frameworks explain parts of the phenomenon but not the whole. TOE explains *whether* organisations adopt AI, but not *how* adoption becomes value. Acceptance models explain individual responses, but not organisational decisions. Implementation frameworks such as CFIR and NASSS are comprehensive but descriptive, and they do not specify testable causal paths. The TOE-HM framework (Figure 3) integrates these contributions into a parsimonious causal structure. It makes two theoretical moves. First, it reconceptualises *implementation barriers* as a boundary condition on the conversion of readiness into adoption, rather than as a mirror image of readiness. This explains why organisations with apparently strong readiness still produce pilots that never scale [10]. Second, it positions *human responses* (attitude and trust) and *decision processes* (decision-making efficiency) as mediating mechanisms downstream of adoption, connecting organisational and individual levels without conflating them.

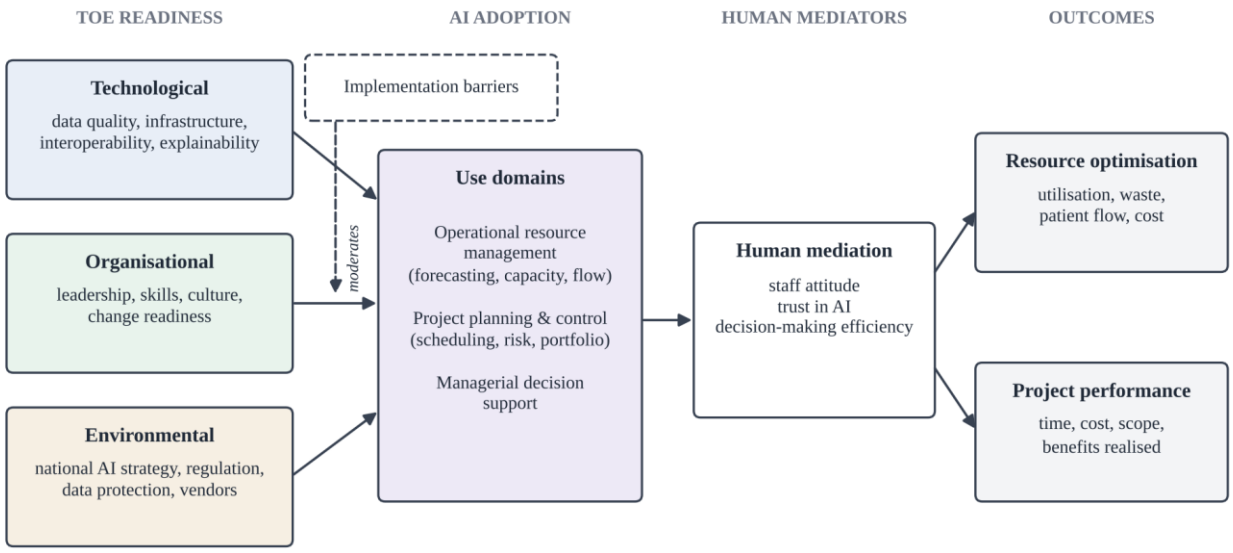

Figure 3: the TOE-HM framework for AI-enabled resource optimisation and project performance in GCC healthcare

5.2 Constructs

Technological readiness is the availability and integration of the data, infrastructure and interoperable systems that AI requires. *Organisational readiness* is the combination of leadership commitment, workforce competence and an innovation-supportive culture [28]. *Environmental support* is the degree to which national policy, regulation and the vendor ecosystem enable AI deployment. *Implementation barriers* are perceived obstacles such as resistance, privacy concerns, integration costs and skills gaps. *AI adoption intensity* is the breadth and depth of AI use across operational resource management, project planning and control, and managerial decision support. *Staff attitude and trust* is the favourable evaluation of AI outputs and the willingness to rely on them. *Decision-making efficiency* is the speed, timeliness and information quality of operational and project decisions. *Resource optimisation* and *project performance* are the outcome constructs defined in Sections 2.1 and 2.2.

5.3 Propositions

- **P1 (Readiness).** Technological readiness, organisational readiness and environmental support are each positively associated with AI adoption intensity in healthcare resource and project management.
- **P2 (Conversion).** Implementation barriers weaken the positive relationship between organisational readiness and AI adoption intensity; at high barrier levels, readiness converts into pilots rather than routine use.
- **P3 (Human mediation).** The effect of AI adoption intensity on resource optimisation is transmitted substantially through staff attitude and trust.
- **P4 (Decision mediation).** The effect of AI adoption intensity on project performance is transmitted substantially through decision-making efficiency.
- **P5 (Outcome linkage).** Resource optimisation is positively associated with project performance, because better allocation reduces delays and rework in projects that share operational resources.
- **P6 (Evidence maturity).** The strength of the observed association between AI adoption and outcomes will decline as evidence maturity rises from perception-based (L2) to comparative outcome measures (L5), reflecting optimism and common-method bias in perception-based studies.

P6 is a methodological proposition that follows from the Evidence-Maturity Ladder. It predicts that published effect sizes in the region, which are largely perception-based, overstate operational value — a pattern consistent with the gap between promised and realised value in documented deployment cases [9, 41].

5.4 Boundary conditions for the GCC

- **BC1 (State-led environment).** Because the state is the funder, provider and regulator, environmental support is expected to have a stronger effect on adoption intensity in public than in private GCC providers, but a weaker effect on outcomes unless matched by organisational readiness.
- **BC2 (Workforce mobility).** High workforce turnover is expected to weaken the staff-attitude pathway (P3) over time, because trust and know-how accumulated by individuals leave with them; organisations that codify AI routines should show more durable effects.
- **BC3 (Regulatory transition).** During the implementation of new personal data protection regimes, data-related barriers are expected to be more salient, strengthening the moderating effect in P2.

VI. Discussion

6.1 Theoretical implications

This paper advances theory in three ways. First, the Evidence-Maturity Ladder offers a reusable instrument for appraising organisational AI evidence. It shifts the question from "how many studies?" to "how far has the evidence progressed towards measured outcomes?". Applied here, it shows that the regional literature has not yet produced comparative outcome evidence. Second, the TOE-HM framework extends TOE from an adoption model into a value model by adding a conversion mechanism and two mediators. This resolves a long-standing level-of-analysis tension between organisational adoption theories and individual acceptance theories [23, 12]. Third, the boundary conditions make the framework context-sensitive. They specify how state-led environments,

workforce mobility and regulatory transition alter the strength of theorised relationships, and they provide testable extensions rather than general appeals to "context".

6.2 Practical implications

For GCC health authorities and hospital executives, four implications follow. (i) **Invest where the evidence is strongest.** Forecasting, capacity, patient flow and administrative automation have the clearest value logic; AI for project management should be piloted with explicit evaluation. (ii) **Treat data integration as the critical path.** Without interoperable, high-quality data, AI cannot optimise resources. (iii) **Budget for the human pathway.** Because attitude and trust carry a substantial share of AI's effect, change management, co-design and training should be funded as core components of AI projects, not as overheads. (iv) **Build evaluation in from the start.** Every AI deployment should define baselines and comparison groups so that it produces L4–L5 evidence. National programmes are well placed to require this as a condition of funding.

6.3 Research agenda

Table 3 sets out a prioritised research agenda derived from the gaps identified.

Table 3: prioritised research agenda

Priority	Research need	Suggested design
1	Comparative evidence of operational outcomes from deployed AI (bed-days, waiting time, utilisation)	Controlled before–after or stepped-wedge evaluation across GCC hospitals
2	Effect of AI on objective healthcare project outcomes (schedule, cost, scope, benefits)	Multi-project panel study using PMO data
3	Test of the TOE-HM structural paths, including mediation and moderation	Multi-country survey with PLS-SEM, adequately powered
4	Evidence from under-represented states (Bahrain, Kuwait, Oman, Qatar)	Comparative case studies; multi-group analysis
5	Test of P6: perceived versus measured effect sizes	Matched survey and administrative data in the same organisations

6.4 Limitations

This is an integrative rather than a systematic review. The corpus was assembled purposively and through targeted searching, and some relevant studies, particularly grey literature and Arabic-language sources, may have been missed. The finding that no source reaches L5 is a statement about this corpus, not a claim that no such study exists. Coding was performed by a single coder. The Evidence-Maturity Ladder is new and requires validation through inter-rater reliability testing. A PRISMA 2020-compliant systematic review with a registered protocol and double coding is recommended to confirm and extend these findings [48].

VII. Conclusion

AI has clear potential to improve how GCC healthcare organisations use scarce resources and manage the projects through which they change. However, appraised against a new Evidence-Maturity Ladder, the evidence for that value is immature. In the GCC it rests largely on announcements, perception surveys and model validation, and no source in the corpus provides comparative outcome evidence. The TOE-HM framework explains why investment has outpaced evidence. AI value depends on technological, organisational and environmental readiness; it is converted into adoption only when barriers are managed; and it is transmitted through the trust of staff and the efficiency of decisions. The framework, its six propositions and three boundary conditions provide a theoretically grounded and testable basis for the next generation of research in the region.

VIII. 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 availability:** The full coding of the review corpus is reported in Appendix Table A1. **Ethics:** Not applicable; this study analyses published literature only.

IX. Appendix

Table A1: coding of the review corpus (n = 26)

Source	Primary domain	Region	Design	Ladder
Kumar et al. (2025) [36]	Operations	GCC	Quantitative	L2
AlMuhaideb et al. (2024) [37]	Operations	GCC	Quantitative	L3
Elnaggar et al. (2023) [34]	Adoption & implementation	GCC	Quantitative	L2
Hamd et al. (2024) [35]	Adoption & implementation	GCC	Quantitative	L2
Karrar et al. (2025) [39]	Operations	GCC	Review	–
Al Kuwaiti et al. (2023) [40]	Clinical	GCC	Review	–
Sharfi (2021) [3]	Policy & governance	GCC	Conceptual / policy	–
MOHAP (2019) [4]	Operations	GCC	Grey / announcement	L0
SEHA Virtual Hospital (2022) [5]	Operations	GCC	Grey / announcement	L0
Khosravi et al. (2024) [8]	Clinical	MENA	Review	–
Chomutare et al. (2022) [43]	Adoption & implementation	International	Review	–
Nair et al. (2024) [44]	Adoption & implementation	International	Qualitative / mixed	L2
Grzeszczyk and Korzeniowski (2025) [20]	Project management	International	Conceptual / policy	L1

Source	Primary domain	Region	Design	Ladder
McInerney et al. (2022) [38]	Operations	International	Conceptual (protocol)	L1
Lee and Yoon (2021) [14]	Operations	International	Review	–
Lee (2024) [49]	Operations	International	Review	–
Bhagat and Kanyal (2024) [15]	Operations	International	Review	–
Secinaro et al. (2021) [7]	Clinical	International	Review	–
Topol (2019) [6]	Clinical	International	Review	–
Strickland (2019) [9]	Clinical	International	Case	L4
Andreassen et al. (2015) [10]	Project management	International	Case	L4
Higgins and Madai (2020) [45]	Adoption & implementation	International	Conceptual / policy	–
Amann et al. (2020) [42]	Adoption & implementation	International	Conceptual / policy	–
Alami et al. (2020) [50]	Policy & governance	International	Conceptual / policy	–
Hillestad et al. (2005) [41]	Operations	International	Quantitative (modelling)	L3
Davenport and Kalakota (2019) [13]	Operations	International	Conceptual / policy	–

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