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AI-ENABLED HEALTH TECHNOLOGY ASSESSMENT AS AN ORGANISATIONAL CAPABILITY SYSTEM: MIXED-METHOD EVIDENCE FROM SAUDI PRIVATE HEALTHCARE

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ABSTRACT

This study examines whether AI-enabled health technology assessment (HTA) improves decision-making effectiveness in Saudi private healthcare directly or mainly through organisational, data, institutional and stakeholder pathways. A sequential explanatory mixed-methods design combined PLS-SEM analysis of 86 survey responses with 15 semi-structured interviews with senior participants involved in strategy, clinical leadership, digital transformation, data, finance, regulation and HTA-related roles. Decision value was mainly mediated. Organisational resources and capabilities significantly strengthened HTA process automation ($\beta = 0.7669$, $p = 0.0064$). Access to quality data showed the strongest total effects and a strong direct effect on regulatory and institutional factors ($\beta = 0.8820$, $p < 0.001$). The direct HTA-process-to-decision path was negligible. Interview evidence showed that HTA functioned as a deliberative support platform whose value depended on data quality, governance legitimacy and stakeholder alignment. The study is cross-sectional and based on a moderate non-probability sample; selected downstream constructs were closely coupled, so the model should be interpreted as explanatory evidence rather than causal proof. Managers should treat AI-enabled HTA as capability building centred on data governance, interoperability, cross-functional governance and stakeholder participation. The article reframes AI-enabled HTA as an organisational capability system and shows that decision value is realised mainly through mediated capability pathways rather than through a simple direct technology effect.

Keywords: AI-enabled HTA; Health Technology Assessment; Organisational Capability; Healthcare Management; Saudi Arabia; Private Healthcare; Mixed Methods

2. INTRODUCTION

Private healthcare organisations in Saudi Arabia are making increasingly consequential decisions about medical devices, digital platforms, analytics tools and service innovations. Under Vision 2030 and wider sector reform, these decisions must satisfy not only clinical expectations but also financial, operational and regulatory criteria (Al-Aqeel, 2018; Mani and Goniewicz, 2024; Al-Jedai et al., 2024). For private providers, the quality of technology decisions now affects investment efficiency, service differentiation, risk exposure and patient trust.

Health technology assessment (HTA) offers a structured way to evaluate technologies across clinical, economic, organisational, ethical and social dimensions (Banta, 2003; O'Rourke et al., 2020; World Health Organization, 2025). Recent advances in artificial intelligence have increased interest in AI-enabled HTA because automation, predictive analytics and evidence-synthesis tools can potentially improve speed, consistency and responsiveness across the assessment cycle (Fleurence et al., 2025; Rose et al., 2025; Ramezani et al., 2025). However, the practical value of AI-enabled HTA is not guaranteed by technology deployment alone. It depends on data quality, organisational capability, governance legitimacy and stakeholder acceptance (Grover et al., 2018; Oortwijn and Klein, 2019; Farah et al., 2024).

That problem is especially visible in Saudi Arabia's private healthcare sector. Existing Saudi scholarship confirms growing interest in formal HTA capability, but it also points to persistent barriers around local data, methodological readiness, stakeholder alignment and institutional development (Al-Aqeel, 2018; Al-Omar et al., 2021; Al-Jedai et al., 2024). More broadly, the international HTA literature still concentrates on public reimbursement, national policy and conventional economic evaluation, with less empirical attention to internal decision processes within private healthcare organisations (O'Rourke et al., 2020). Work on AI in HTA has similarly focused more on technical promise than on empirically tested organisational outcomes (Fleurence et al., 2025; Ramezani et al., 2025).

These gaps matter for management research because private providers face a different decision environment from national reimbursement bodies. Decision cycles are shorter, investment logics are more commercially exposed, adoption choices must fit organisational workflows and digital infrastructures, and implementation credibility depends on whether multiple internal actors are willing to act on the assessment. In such settings, the question is not only whether HTA can generate evidence, but whether organisations can translate that evidence into legitimate and actionable decisions.

This article addresses that gap by testing and explaining a mediation-based framework of AI-enabled HTA in Saudi private healthcare. The study asks a simple but important question: does AI-enabled HTA improve decision-making effectiveness directly, or mainly through the organisational conditions that allow evidence to be trusted and acted on? The article makes three contributions. First, it develops a system-level explanation of AI-enabled HTA by integrating Decision Theory, the Resource-Based View (RBV) and Institutional Theory. Second, it provides mixed-method evidence from an under-researched private healthcare setting. Third, it translates the findings into a managerial logic for implementation, showing why data quality, organisational readiness and stakeholder engagement matter more than software acquisition alone.

Internationally, HTA has become an established mechanism for evidence-informed prioritisation in a number of systems, yet implementation remains uneven and context-dependent. Studies from the United Kingdom, Singapore, South Africa and Kenya show that effective HTA depends on more than methodological guidance alone; it requires organisational sponsorship, local data, clear governance and institutional support (Mueller, 2020; Segar et al., 2021; Mbau et al., 2023). These lessons are highly relevant to private healthcare markets where decision cycles are shorter, technologies are heterogeneous and investment logics differ from public reimbursement settings.

Saudi Arabia provides a particularly important case. The country's health-sector transformation programme has accelerated digitalisation, private-sector participation and interest in value-based decision-making. Private providers are under pressure to adopt technologies ranging from robotic platforms and telemedicine systems to advanced diagnostics and enterprise analytics, while simultaneously demonstrating value for money and compliance readiness (Al-Aqeel, 2018; Al-Omar et al., 2021; Mani and Goniewicz, 2024). In such settings, HTA has the potential to become a strategic management capability rather than a narrow policy tool.

3. Theoretical background and research framework

Decision Theory explains why HTA matters in the first place. Technology decisions in healthcare are made under uncertainty, involve competing criteria and create consequences that extend beyond acquisition cost. HTA supports such decisions by structuring appraisal around evidence, trade-offs and justified choice (March, 1994; Drummond et al., 2008; Krahn et al., 2018). In AI-enabled form, HTA can accelerate evidence handling and support more disciplined comparison of alternatives, but it does not eliminate managerial judgement.

RBV adds the capability dimension. Organisations differ in the resources that allow them to turn analytical tools into decision value. In the present study, organisational resources and capabilities (ORC) include leadership commitment, governance routines, digital infrastructure, expertise and implementation capacity, while access to quality data (AQD) includes data accuracy, completeness, timeliness, interoperability and security. From an RBV perspective, these are not background conditions; they are strategic assets that shape whether AI-enabled HTA becomes operationally useful (Barney, 1991; Grover et al., 2018; Teece, 2018).

Institutional Theory explains why technically credible assessment does not automatically translate into action. Organisations adopt and use HTA within a field shaped by regulation, professional norms, accreditation expectations and legitimacy pressures (Scott, 2014; Mbau et al., 2023). In private healthcare, decision-makers must often secure acceptance across executives, clinicians, finance functions, digital teams and external authorities. Stakeholder engagement in HTA (SEHTA) therefore matters because it converts analysis into approval, implementation and sustained use (Gagnon et al., 2006; Gauvin et al., 2014; Oortwijn and Klein, 2019).

Taken together, these three lenses support a mediated capability architecture rather than a simple input-output model. The framework tested in this study links HTA process automation (HTPA) with decision-making effectiveness (EDM) through ORC, AQD, regulatory and institutional factors (RIF) and SEHTA. The core expectation is that AI-enabled HTA will create value most convincingly when data quality, organisational capability, regulatory legitimacy and stakeholder alignment work together. This framing moves the debate away from technological determinism and toward a socio-organisational explanation of AI-enabled decision support.

HTPA captures the extent to which assessment tasks such as evidence synthesis, economic modelling and clinical-effectiveness review are digitally supported or semi-automated. ORC captures the extent to which the organisation possesses the leadership, expertise, infrastructure and routines needed to use such assessment credibly. AQD captures the quality of the information base available to HTA, RIF captures the formal and normative environment in which decisions are taken and SEHTA captures the participation and alignment of actors who influence adoption and implementation. EDM is the final outcome, defined in this study as the degree to which technology-related decisions are timely, evidence-based, strategically aligned and operationally actionable.

This construct architecture draws on prior work showing that hospital-based HTA, digital-health evaluation and value-based procurement often fail when they are treated as purely technical exercises (Grossi et al., 2021; Pascal et al., 2022; Farah et al., 2024). The model therefore places less emphasis on whether AI tools can perform assessment tasks in principle and more emphasis on whether organisations can absorb their outputs into legitimate decision routines. That distinction is especially relevant for management research, because the problem is not simply analytical accuracy but organisational translation.

The framework therefore implies differentiated roles for the constructs. AQD and ORC are expected to behave as enabling resources, RIF as a legitimacy-setting context, HTPA as the operating mechanism within assessment work and SEHTA as the translation mechanism through which technically credible analysis becomes collectively acceptable action. This theoretical architecture informed both the quantitative model and the qualitative interview prompts. Figure 1 presents the conceptual model of the study.

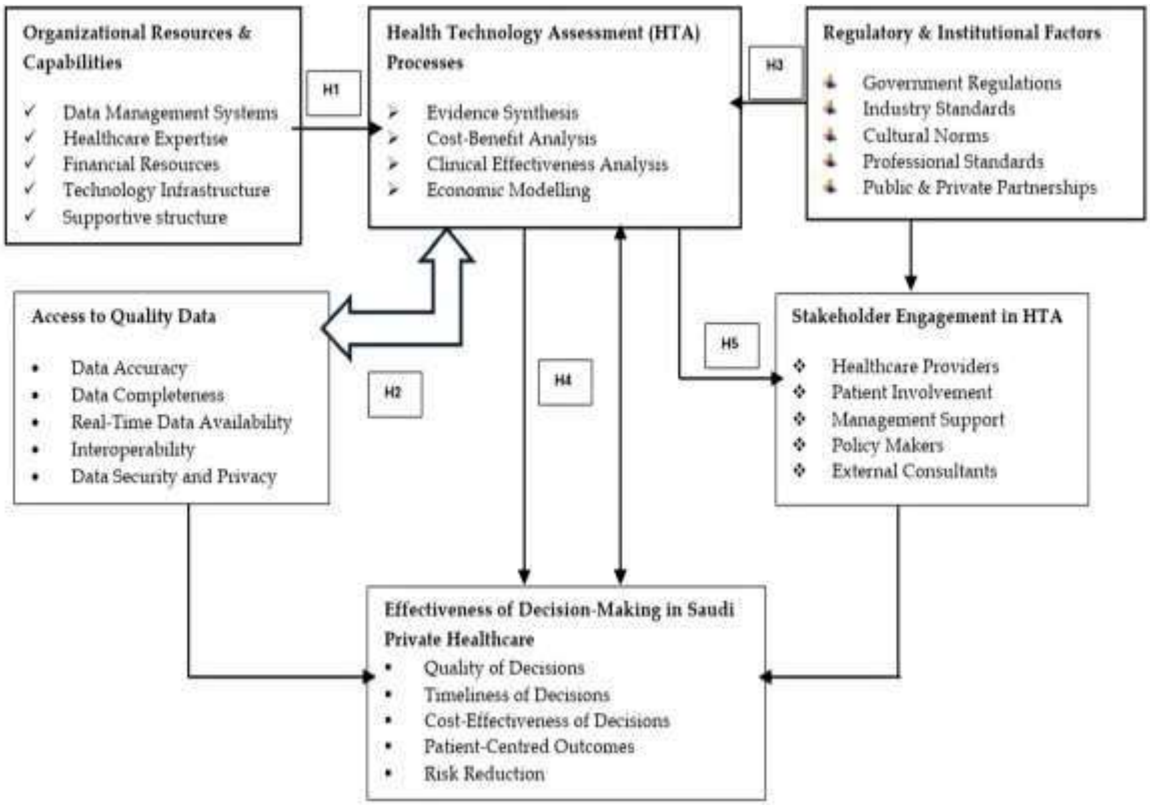

Figure 1. Conceptual model of the AI-enabled HTA capability system.

4. Methods

The study adopted a sequential explanatory mixed-methods design. A quantitative survey was used first to test relationships among the core constructs, and a qualitative interview phase was then used to explain the resulting structural pattern. This design was appropriate because the research problem contained both a structural question (which relationships matter) and an explanatory question (how those relationships operate in practice).

The quantitative phase used a cross-sectional questionnaire administered to professionals working in Saudi Arabia's private healthcare sector. The instrument employed five-point Likert-scale items covering HTPA, ORC, RIF, AQD, SEHTA and EDM. Items were derived from the literature and refined through expert review and a pilot involving 20 domain specialists. Survey distribution relied on professional networks and snowball sampling. Of 103 initial responses, 86 were retained after screening for completeness, duplication and response quality. The validated sample included respondents from biomedical engineering, informatics, procurement, nursing and pharmacy roles, with representation from private hospitals, clinics and diagnostic centres across Saudi regions.

The sample was designed for analytical rather than statistical generalisation. The purpose was to estimate the behaviour of the conceptual model within an information-rich professional sample rather than to produce prevalence estimates for the entire private-healthcare population. This is consistent with the use of PLS-SEM in exploratory and prediction-oriented settings where theory development and model complexity are central objectives (Hair et al., 2014; Hair et al., 2019). It also explains why the subsequent interpretation focuses on pathway structure and relative explanatory weight rather than on population claims.

The qualitative phase comprised 15 semi-structured interviews with senior participants selected purposively for their relevance to technology decisions and HTA-related processes. Interviewees represented digital transformation, strategy, regulatory oversight, clinical leadership, data and analytics, finance and HTA committee functions. This senior sample was intentionally different from the broader survey sample: the quantitative strand captured organisation-level perceptions across operational and managerial roles, whereas the qualitative strand was used to probe mechanism, implementation logic and decision dynamics from participants with direct strategic visibility.

Quantitative analysis was undertaken in SPSS and ADANCO. After initial data screening, the PLS-SEM analysis proceeded in two stages: assessment of the measurement model and estimation of the structural model. Reliability was examined using Dijkstra-Henseler's rho (rhoA), Joreskog's rho and Cronbach's alpha. Convergent validity was assessed through average variance extracted (AVE).

Structural analysis used path coefficients, effect sizes, explained variance and ADANCO's bias-corrected bootstrap inference, with two-sided significance testing and percentile bounds used to evaluate direct, indirect and total effects (Hair et al., 2014; Hair et al., 2019; Sarstedt et al., 2017).

Instrument development was theory driven. HTPA items covered evidence synthesis, cost-benefit analysis, clinical-effectiveness assessment and economic modelling; ORC items addressed healthcare expertise, financial and digital resources, supportive structures and implementation capability; AQD items covered accuracy, completeness, real-time availability, interoperability and security; RIF items addressed regulations, standards and professional expectations; SEHTA items addressed provider involvement, management support, policy participation and external expertise; and EDM items focused on decision quality, timeliness, cost-effectiveness, patient-centredness and risk reduction. The pilot process was used to remove ambiguous or overlapping wording and to sharpen construct separation before the final survey was launched. To reduce common-method bias at the design stage, the survey was anonymous, no names, email addresses or hospital identifiers were collected, and confidentiality and voluntary participation were stated explicitly.

Because several constructs are conceptually adjacent in organisational settings, measurement distinctiveness was assessed conservatively. In addition to reliability and AVE, the diagnostic assessment examined Fornell-Larcker comparisons, inter-construct correlations, indicator-level variance inflation factors and HTMT inspection (Fornell and Larcker, 1981; Henseler et al., 2017). This step was important because data quality, stakeholder engagement and decision effectiveness can be strongly coupled in practice. Selected downstream pairs showed substantial proximity, so the analysis treated discriminant validity as a matter of degree rather than as a purely binary pass-fail exercise.

The item-level VIF values remained within conventional tolerance levels, indicating that indicator collinearity was not the dominant source of the observed structural pattern. However, strong correlations among some downstream constructs meant that the model had to be interpreted as a closely connected capability architecture rather than as a set of sharply isolated causal blocks. This interpretive discipline is especially important when the final outcome exhibits a high proportion of explained variance.

Interview recordings were transcribed verbatim and analysed thematically through iterative coding, refinement and comparison across cases. The coding process began with theory-informed first-cycle categories linked to the study constructs, then moved to interpretive themes that explained why certain direct paths were weak, why others worked through mediation and how HTA recommendations were translated into actual decisions. Illustrative quotations were selected sparingly to represent each final theme and to show how the interview evidence anchored the integrated interpretation. Integration occurred through triangulation, linking the major quantitative results with qualitative explanations rather than treating the two strands as parallel but disconnected exercises.

The mixed-method design was chosen to match the applied nature of the research problem. A purely quantitative design would have allowed structural testing but would have provided limited leverage on why some seemingly plausible direct effects might fail to materialise. A purely qualitative design, by contrast, would have offered insight into context and meaning but would have reduced the ability to test the broader structural architecture. The sequential explanatory design allowed the study to retain both breadth and mechanism-focused interpretation.

Ethical review was completed through the author's institutional ethics review process before data collection commenced (approval date: 6 April 2026). The institutional review documentation available to the author does not list a separate approval number. The study complied with the institution's requirements for research involving human participants. Participants in both phases were informed of the purpose of the research, the voluntary nature of participation, confidentiality protections and data-handling arrangements. Informed consent was obtained from all survey respondents and interview participants, and identifying information was removed from the analytical reporting.

5. Findings

The sample profile indicates a relatively young but professionally relevant respondent base. Most respondents were aged 21-30 years (62.4 per cent), 52.9 per cent reported less than three years of healthcare-sector experience and 51.8 per cent held master's degrees. Familiarity with HTA processes was moderate overall: 22.4 per cent were very familiar, 54.1 per cent somewhat familiar and 23.5 per cent not familiar. These characteristics suggest exposure to digital and operational healthcare roles rather than to HTA-specialist populations alone, which is helpful for understanding how HTA is perceived across the wider decision environment.

Construct-level descriptive statistics showed moderate but positive perceptions across the model.

RIF recorded the highest mean (3.4714), followed by AQD and EDM, while HTPA recorded the lowest mean (3.3146). AQD and EDM also showed comparatively low dispersion, indicating that respondents were more consistent in their views about data quality and decision effectiveness than about the maturity of automated HTA processes. This pattern is substantively meaningful because it suggests that respondents recognised the importance of evidence quality even where formal HTA routines remained uneven.

The measurement model showed strong internal consistency. Cronbach's alpha values ranged from 0.8758 to 0.9379, Dijkstra-Henseler's rho from 0.8805 to 0.9404 and Joreskog's rho from 0.8766 to 0.9371. AVE values ranged from 0.5010 to 0.5935, indicating acceptable convergent validity across the six constructs. The explained variance of the endogenous constructs was also substantial, especially for EDM (R^2 = 0.9032), SEHTA (R^2 = 0.8134), RIF (R^2 = 0.7780) and HTPA (R^2 = 0.6671). Table I reports the principal reliability and variance-explained statistics.

Table I. Measurement quality and explained variance

Construct	Cronbach's alpha	AVE	R^2
HTPA	0.9379	0.5010	0.6671
ORC	0.9324	0.5759	0.5955
RIF	0.9340	0.5849	0.7780
AQD	0.8758	0.5177	–

SEHTA	0.9063	0.5935	0.8134
EDM	0.8895	0.5473	0.9032

Notes: HTPA = HTA process automation; ORC = organisational resources and capabilities; RIF = regulatory and institutional factors; AQD = access to quality data; SEHTA = stakeholder engagement in HTA; EDM = decision-making effectiveness; AQD is exogenous in the final model, so R^2 is not applicable. Additional diagnostics showed strong downstream proximity, particularly AQD–EDM = 0.9014 and SEHTA–EDM = 0.9317; EDM's AVE (0.5473) was lower than its squared correlations with AQD (0.8125) and SEHTA (0.8681), so the results were interpreted cautiously as a tightly connected capability system.

At the same time, the diagnostic picture was not entirely frictionless. Strong inter-construct correlations were observed among some downstream variables, especially AQD with EDM (r = 0.9014) and SEHTA with EDM (r = 0.9317), and selected HTMT inspections approached conventional thresholds. In the Fornell-Larcker comparison, EDM's AVE (0.5473) was lower than its squared correlations with AQD (0.8125) and SEHTA (0.8681). These patterns do not nullify the model, but they do mean that the very high R^2 for decision effectiveness should be interpreted cautiously as evidence of a tightly connected organisational capability architecture rather than of sharply isolated latent domains.

The structural results do not support a simple direct-effect interpretation. ORC exerted a strong and statistically significant direct effect on HTPA (β = 0.7669, p = 0.0064), indicating that HTA maturity depends heavily on leadership support, governance routines, expertise and infrastructure. AQD had an exceptionally strong direct effect on RIF (β = 0.8820, p < 0.001), suggesting that the institutional usability of HTA is tightly connected to the underlying data environment.

The most important pattern, however, lies in the total effects. AQD showed a significant total effect on HTPA (β = 0.6138, p < 0.001), ORC (β = 0.7268, p < 0.001), SEHTA (β = 0.8721, p < 0.001) and EDM (β = 0.9044, p < 0.001). AQD therefore operated as the dominant upstream enabler in the estimated system. By contrast, the direct HTPA-to-EDM path was negligible (β = 0.0073, p = 0.9840). Other direct paths were positive in magnitude but were not independently supported in the bootstrap inference tables, including SEHTA-to-EDM, AQD-to-EDM and RIF-to-ORC. Figure 2 presents the validated structural model estimated in ADANCO.

Table II. Key structural effects supporting the mediated capability interpretation

Path	Direct β	Total β	Interpretation
ORC → HTPA	0.7669	0.7669	Significant direct effect (p = 0.0064)
AQD → RIF	0.8820	0.8820	Highly significant direct effect (p < 0.001)
AQD → HTPA	–	0.6138	Significant total effect (p < 0.001)
AQD → ORC	0.2412	0.7268	Significant at total-effect level (p < 0.001)
AQD → SEHTA	0.5210	0.8721	Significant at total-effect level (p < 0.001)
AQD → EDM	0.3769	0.9044	Significant at total-effect level (p < 0.001)
HTPA → EDM	0.0073	0.1465	Negligible and not significant
SEHTA → EDM	0.5997	0.5997	Positive but not significant alone

Note: The strongest statistical support is concentrated in AQD-led total effects and the direct ORC → HTPA relationship; direct paths to EDM were weak in isolation.

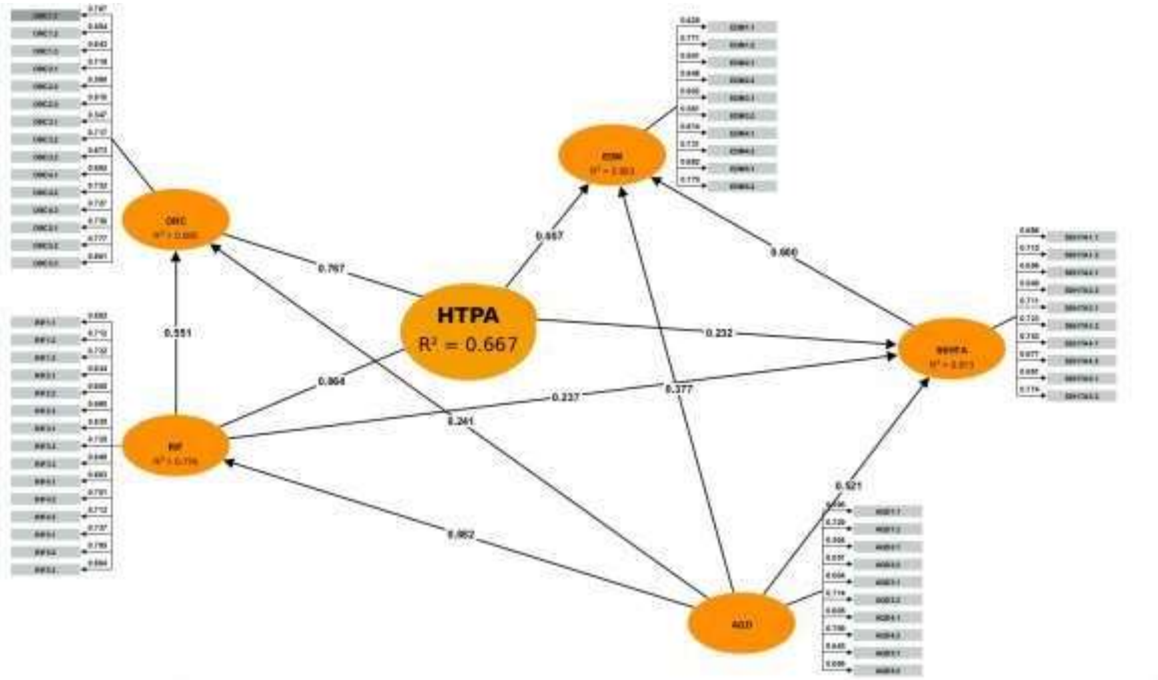

Figure 2. Validated structural model estimated in ADANCO.

The qualitative findings deepened this interpretation rather than contradicting it. Five themes were consistently identified, and Table III reports these themes together with exemplar interview evidence. First, HTA was described as a deliberative decision-support platform rather than an autonomous decision authority. Interviewees repeatedly stressed that HTA reports inform committees and executives, but do not 'make' the decision on their own. As one strategy director put it, 'HTA reports do not make decisions by themselves. They create a platform for discussion.' Second, organisational capability was treated as a precondition for HTA value realisation.

Third, data quality emerged as the dominant upstream enabler. Fragmented data, poor interoperability and delayed access to cost and clinical information were described as the main practical barriers to effective AI-enabled HTA. One Chief Digital Officer stated that 'AI HTA is only as good as the data behind it', while another interviewee called 'data integration and trust in data' the main bottleneck. Fourth, regulatory and institutional alignment acted as a boundary-setting influence rather than as a direct decision driver; as one regulatory adviser noted, regulation sets 'the boundaries within which decisions must be made'. Fifth, stakeholder engagement was portrayed as the mechanism that converts analysis into approval and execution, captured by the observation that 'stakeholder buy-in is what turns analysis into approval.'

Table III. Integrated qualitative themes and illustrative interview evidence

Theme	Illustrative interview evidence and integrated explanation	Managerial reading
HTA as a deliberative support platform	[Senior hospital strategy director] "HTA reports do not make decisions by themselves. They create a platform for discussion." Explained why the direct HTPA → EDM path was negligible despite positive total influence.	Use AI-enabled HTA to inform committees and executives, not to replace managerial judgement
Organisational capability as a precondition	[HTA committee member] "Even if the analysis is technically perfect, decisions depend on whether the organisation has the capability and confidence to act on it." Explained the strong ORC → HTPA relationship.	Invest in expertise, governance routines, digital infrastructure and implementation capacity

Data quality as the dominant upstream enabler	[Chief Digital Officer] "AI HTA is only as good as the data behind it." A second interviewee emphasised that "the biggest bottleneck is not analytics capability; it is data integration and trust in data." Explained the strong AQD total effects and the AQD → RIF relationship.	Prioritise interoperability, stewardship and timely access to clinical, operational and cost data
Regulatory and institutional alignment as a boundary condition	[Regulatory adviser] "Regulation does not tell hospitals what decision to make. It tells them the boundaries within which decisions must be made." Explained why RIF mattered directionally even when isolated direct effects were weak.	Align evidence standards, compliance expectations and approval pathways
Stakeholder engagement as a translation mechanism	[Senior clinician] "If doctors do not trust the HTA process, the decision will not move—regardless of the numbers." [Finance executive] "Stakeholder buy-in is what turns analysis into approval." Explained why SEHTA remained practically important despite a weak isolated bootstrap result.	Secure clinician buy-in, executive sponsorship and cross-functional participation

Note: Themes were derived from the 15 explanatory interviews; short quotations are included with anonymised role labels so the qualitative evidence is visible without identifying organisations or individuals.

The mixed-method integration therefore points to a clear conclusion. AI-enabled HTA contributes to decision-making effectiveness through a connected system of enablers rather than through a direct technological effect. High-quality data strengthens organisational capability and institutional alignment; organisational capability strengthens HTA processes; and stakeholder engagement helps convert technically credible analysis into decisions that can be implemented. The statistical results and interview themes converge most clearly on this system-level reading.

This interpretation also explains the apparent tension between a very high final R^2 and several weak direct paths. In practical terms, the model is capturing the fact that decision effectiveness in private healthcare is a joint outcome of multiple tightly coupled conditions. What matters is not a single dominant route from automated assessment to decision, but whether the organisation has the informational, organisational and legitimacy conditions needed to act on assessment outputs.

6. Discussion

The first contribution of the study is conceptual. The findings suggest that AI-enabled HTA is better understood as an organisational capability system than as a stand-alone analytical tool. This matters because the literature often treats AI-enabled assessment as if automation itself should improve decisions. The present evidence does not support that interpretation. Instead, the weak HTPA-to-EDM path shows that assessment activity is necessary but not sufficient. HTA becomes influential when evidence is embedded in a wider architecture of data, capability, legitimacy and stakeholder conversion.

This interpretation extends Decision Theory in an applied healthcare-management setting. Decision Theory explains why structured appraisal is needed under uncertainty, but the present study shows that structured appraisal alone does not secure effective decisions. The translation from analysis to action depends on whether decision-makers trust the inputs, understand the outputs and recognise the governance legitimacy of the process. In this sense, the study bridges analytical rationality with organisational reality.

The second contribution lies in the centrality of data quality. AQD was the strongest construct in total-effect terms and the strongest direct driver of the institutional environment. This result is consistent with the view that data infrastructure is a strategic resource rather than a technical back-office function (Grover et al., 2018; Kent et al., 2021). In AI-enabled HTA, poor-quality data does not merely weaken measurement precision; it undermines legitimacy, slows deliberation and reduces the likelihood that recommendations will be implemented. For managers, this means that data governance and interoperability are not supporting investments at the margin; they are the foundation of credible HTA.

The third contribution concerns organisational capability. ORC did not improve EDM directly, but it significantly strengthened HTPA. This pattern aligns closely with RBV. Leadership commitment, expertise, governance arrangements and digital readiness act as capability multipliers that allow HTA to be performed consistently and interpreted credibly. Private healthcare organisations that treat HTA as an isolated analytical task are therefore likely to underperform compared with organisations that institutionalise it through routines, committees, decision rights and cross-functional ownership.

The fourth contribution involves the role of institutions and stakeholders. RIF did not emerge as a stand-alone direct driver of EDM, yet the qualitative evidence clearly indicates that regulation and professional norms shape what evidence is acceptable, how quickly decisions move and which actors must be satisfied. Likewise, SEHTA showed large practical importance even where separate statistical significance was not achieved. This apparent tension is best interpreted as a systems effect. Stakeholder engagement matters because it converts technically credible analysis into decisions that are accepted and executed, even if its influence is not well described by a simple isolated direct path.

These findings also extend the HTA literature beyond public reimbursement and national policy design. Most established HTA research centres on public-sector decision systems, whereas this study examines internal decision-making in private healthcare organisations. The results suggest that, in private settings, HTA operates less as a one-off evaluation document and more as an organisational governance process. That shift in emphasis matters for health-organisation scholarship because it connects HTA with broader debates about digital transformation, managerial capability and organisational legitimacy.

The managerial reading of the model is straightforward. Organisations should build AI-enabled HTA through a maturity sequence. The first stage is data reliability and interoperability. The second is governance capability: clear decision rights, analytical expertise, implementation ownership and multidisciplinary participation. The third is institutional and stakeholder alignment so that recommendations are legitimate enough to move from analysis to action. From this perspective, software acquisition is an enabler, but not the centre of the implementation problem.

The Saudi context gives this contribution additional relevance. The private sector is expanding under a reform agenda that expects providers to justify technology investment in both strategic and operational terms. In such an environment, the study suggests that AI-enabled HTA can become a bridge between digital transformation rhetoric and disciplined resource-allocation practice. The bridge holds, however, only when organisations can align evidence standards, governance routines and data architecture with the pace of private-sector decision-making.

The findings also carry policy implications. Regulators and sector leaders seeking to strengthen HTA in Saudi private healthcare should focus not only on rules and mandates but also on enabling conditions. Shared data standards, methodological guidance, interoperable information infrastructures and clearer expectations for evidence review would likely strengthen the credibility and consistency of HTA across organisations. Such measures would also reduce the risk that AI-enabled assessment becomes symbolic rather than operational.

For health-organisation scholars, the study offers a methodological contribution as well. The explanatory strength of the model rests less on any single direct coefficient than on the pattern of mediated and total effects. This shows why mixed-methods designs are valuable for management questions involving new digital capabilities. The survey identifies where explanatory weight is concentrated, while the interviews explain why some relationships are indirect, conditional or weak when examined one path at a time.

A further implication concerns how organisations should evaluate vendor claims about AI-enabled solutions. Vendors often present AI as if analytical sophistication alone will improve adoption decisions. The present evidence suggests a different standard: managers should ask whether the proposed tool will improve data quality, integrate with governance routines, support cross-functional deliberation and strengthen rather than bypass stakeholder trust. A technically impressive tool that cannot be integrated into these conditions is unlikely to improve decision effectiveness sustainably.

At the same time, the discussion should not over-read the model. The very high explained variance for EDM and the strong proximity of some constructs indicate that respondents may have viewed several downstream organisational conditions as mutually reinforcing parts of one broader capability system. Because several perceptual measures were collected in the same survey wave, some common-method inflation cannot be ruled out, even though the design reduced that risk through an anonymous survey, removal of identifying fields and pilot refinement of ambiguous or overlapping items. That is substantively interesting, but it also means the findings are better treated as configuration evidence than as definitive proof of sharply separable causal effects. The study therefore contributes a plausible organisational explanation with strong managerial relevance, while still leaving room for more stringent future testing.

7. Practical implications

The findings support four immediate managerial actions. First, organisations should begin with data governance: data definitions, interoperability standards, stewardship roles and secure access to cost, clinical and operational data. Second, they should formalise HTA governance through cross-functional committees or decision forums that include clinical, operational, financial, digital and risk perspectives. Third, they should standardise evidence criteria so that technology proposals are assessed consistently rather than through ad hoc persuasion or vendor pressure. Fourth, they should embed implementation review into the HTA cycle so that post-adoption outcomes inform future appraisal decisions.

The study also offers guidance for regulators and policymakers. Rather than treating HTA primarily as a compliance exercise, regulators can accelerate value-based adoption by supporting capability-building, methodological guidance and shared data infrastructures. A more enabling policy approach would likely improve decision consistency across organisations and reduce duplication of assessment effort.

For investors and boards, the results suggest that rigorous AI-enabled HTA should be treated as a risk-mitigation mechanism that improves capital allocation and protects against symbolic or poorly integrated technology adoption. The managerial priority is therefore not simply to buy an AI-enabled assessment platform, but to create the capability conditions under which that platform can generate trusted, timely and implementable recommendations.

8. Limitations and future research

The study has important limitations. First, the quantitative phase relied on a moderate non-probability sample, which is suitable for exploratory PLS-SEM but limits statistical generalisability. The respondent profile was also relatively young and not limited to HTA specialists, so the results should be read as organisation-level perception evidence rather than as a census of expert judgement.

Second, the research is cross-sectional and therefore captures perceptions at one point in time rather than the evolution of HTA maturity. Third, the setting is confined to Saudi private healthcare, so transferability to public systems or other countries should be made carefully. Fourth, downstream construct proximity remained high, with correlations of 0.9014 between AQD and EDM and 0.9317 between SEHTA and EDM, and selected HTMT inspections were borderline; the same-source survey design also means common-method inflation cannot be ruled out. The structural findings should therefore be interpreted as strong explanatory patterns rather than as final causal proof. This is particularly relevant when considering the high R^2 for EDM.

Fifth, the qualitative strand was designed for explanation rather than representativeness. Interviewees were purposively selected senior participants who could explain organisational mechanisms, but that design may underrepresent frontline clinical and procurement perspectives. The qualitative evidence nevertheless adds substantial value because it clarifies how the statistical pattern maps onto actual governance and implementation practices.

Future research should therefore pursue longitudinal designs, compare public and private settings and test whether the relative importance of AQD, ORC, RIF and SEHTA changes as HTA becomes more mature. More fine-grained studies could also examine technology-specific use cases such as AI diagnostics, telemedicine and hospital-based procurement. Finally, linking HTA maturity with observed post-adoption outcomes—for example implementation speed, budget variance or realised operational value—would strengthen the business case for capability investment.

9. Conclusion

AI-enabled HTA does not improve decisions simply because analytic tools are present. In Saudi Arabia's private healthcare sector, its effectiveness depends on whether organisations can convert evidence into action through data quality, organisational capability, regulatory legitimacy and stakeholder alignment. The strongest empirical support in this study is therefore not for a direct HTA effect, but for a mediated capability architecture in which access to quality data is the dominant upstream driver.

For healthcare leaders, the practical lesson is clear: govern AI-enabled HTA as an organisational capability-development agenda, not as a procurement exercise. Organisations that strengthen data foundations, cross-functional governance and stakeholder participation are more likely to turn assessment into defensible and effective technology decisions. That translation from analytics to action is the central contribution of AI-enabled HTA in private healthcare.

10. Ethics statement

Ethical review was completed through the author's institutional ethics review process on 6 April 2026. The institutional record available to the author does not list a separate approval number. The study complied with the institution's requirements for research involving human participants. All participants received study information and provided informed consent before participation; confidentiality protections and data-handling arrangements were explained in advance, and identifying information was removed from the analytical reporting.

11. Data availability statement

The survey results are reported in aggregated form in the article. Interview transcripts are not publicly available because they contain potentially identifying organisational information. Extended diagnostic tables and additional analytical materials can be made available by the author on reasonable request, subject to institutional and confidentiality constraints.

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