



ARTICLE



COMPETITIVE INTELLIGENCE CAPABILITY FOR TECHNOLOGY-ADOPTION DECISIONS: AN INTELLIGENCE-CYCLE FRAMEWORK FOR PUBLIC-SECTOR AI ADOPTION

CAPACIDADE DE INTELIGÊNCIA COMPETITIVA PARA DECISÕES DE ADOÇÃO DE TECNOLOGIA: UM MODELO DE CICLO DE INTELIGÊNCIA PARA A ADOÇÃO DE INTELIGÊNCIA ARTIFICIAL NO SETOR PÚBLICO

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How to cite this article:

Xing, Y., Biibosunova, S., Liu, F., & Zheng, X. (2026). Competitive Intelligence Capability for Technology-Adoption Decisions: An Intelligence-Cycle Framework for Public-Sector AI Adoption. *Journal of Sustainable Competitive Intelligence*, 16, e0491. <https://doi.org/10.37497/eagleSustainable.v16i.491>

ABSTRACT

Purpose: This study operationalises competitive intelligence (CI) as a measurable organisational capability for strategic technology-adoption decisions. It uses the intelligence cycle to structure how a public-sector organisation collects, analyses, governs, and acts on signals about a new technology, here artificial intelligence (AI), and tests this capability model empirically.

Methodology/Approach: A reflective partial least squares structural equation model (PLS-SEM) is estimated on an open primary survey of 203 mid and senior government officials across the six Gulf Cooperation Council (GCC) countries. The analysis reports exploratory factor analysis, KMO and Bartlett tests, reliability and convergent validity, discriminant validity by the Fornell-Larcker and HTMT criteria with bootstrap inference, collinearity diagnostics, 5,000-sample bootstrap path estimation, mediation, effect sizes, and cross-validated predictive relevance.

Originality/Relevance: The study moves CI from an interpretive frame to an empirically validated capability model in a genuine organisational, non-educational setting, connecting the intelligence cycle, intelligence governance, dynamic capabilities, and decision intelligence to a strategic technology-adoption outcome.

Key findings: The capability dimensions explain 70 percent of the variance in strategic AI outcomes, with strong predictive relevance (Q-squared = 0.68). Technical infrastructure, the collection backbone, is the dominant driver (beta = 0.66) and governance contributes significantly (beta = 0.21), while organisational readiness is a condition built by infrastructure and governance rather than an independent driver. All constructs show high reliability (alpha 0.92 to 0.96) and convergent validity (AVE 0.87 to 0.94), and discriminant validity holds under the HTMT inference criterion.

Theoretical/methodological contributions: The paper contributes a transferable operationalisation of the intelligence cycle as a validated structural model, a governance-centred reading of technology-adoption decisions, and a reproducible CI measurement template applicable across organisational contexts.

Keywords: Competitive intelligence. Intelligence cycle. Intelligence governance. Dynamic capabilities. Decision intelligence. Technology-adoption decision. PLS-SEM. Public-sector artificial intelligence.



DOI: <https://doi.org/10.37497/eagleSustainable.v16i.491>





RESUMO

Objetivo: Este estudo operacionaliza a inteligência competitiva (IC) como uma capacidade organizacional mensurável para decisões estratégicas de adoção de tecnologia. Utiliza o ciclo de inteligência para estruturar como uma organização do setor público coleta, analisa, governa e age sobre sinais relativos a uma nova tecnologia, neste caso a inteligência artificial (IA), e testa empiricamente esse modelo de capacidade.

Metodologia/Abordagem: Um modelo de equações estruturais por mínimos quadrados parciais (PLS-SEM) reflexivo é estimado a partir de uma pesquisa primária aberta com 203 funcionários públicos de nível médio e sênior nos seis países do Conselho de Cooperação do Golfo (CCG). A análise reporta análise fatorial exploratória, testes KMO e de Bartlett, confiabilidade e validade convergente, validade discriminante pelos critérios de Fornell-Larcker e HTMT com inferência por bootstrap, diagnósticos de colinearidade, estimação de caminhos por bootstrap de 5.000 reamostragens, mediação, tamanhos de efeito e relevância preditiva validada por validação cruzada.

Originalidade/Relevância: O estudo desloca a IC de uma lente interpretativa para um modelo de capacidade validado empiricamente em um contexto organizacional real e não educacional, conectando o ciclo de inteligência, a governança da inteligência, as capacidades dinâmicas e a inteligência de decisão a um resultado estratégico de adoção de tecnologia.

Principais resultados: As dimensões da capacidade explicam 70 por cento da variância nos resultados estratégicos de IA, com forte relevância preditiva (Q -quadrado = 0,68). A infraestrutura técnica, a base de coleta, é o principal determinante (β = 0,66) e a governança contribui de forma significativa (β = 0,21), enquanto a prontidão organizacional é uma condição construída pela infraestrutura e pela governança, e não um determinante independente. Todos os construtos apresentam alta confiabilidade (α de 0,92 a 0,96) e validade convergente (AVE de 0,87 a 0,94), e a validade discriminante é sustentada pelo critério de inferência HTMT.

Contribuições teóricas/metodológicas: O artigo contribui com uma operacionalização transferível do ciclo de inteligência como um modelo estrutural validado, uma leitura centrada na governança das decisões de adoção de tecnologia e um modelo de mensuração de IC reproduzível aplicável a diferentes contextos organizacionais.

Palavras-chave: Inteligência competitiva. Ciclo de inteligência. Governança da inteligência. Capacidades dinâmicas. Inteligência de decisão. Decisão de adoção de tecnologia. PLS-SEM. Inteligência artificial no setor público.

1 INTRODUCTION

Competitive intelligence (CI) is widely understood as the organisational capability to collect, analyse, and act on information about the external environment in order to inform strategic decisions (Cavallo et al., 2021; Ibrahim et al., 2025). Recent scholarship frames it not as an occasional study but as a continuous, governed process that turns dispersed signals into decision-relevant insight and, ultimately, into sustainable competitive advantage (Cavallo et al., 2021; Adomako & Tran, 2022). A recurring problem in the field is that this capability is theorised richly but measured rarely. CI is often described through narrative or conceptual accounts of the intelligence cycle, while the cycle itself is seldom expressed as a validated empirical model of

the decisions it exists to inform. This study addresses that gap directly. It treats CI as a measurable organisational capability and operationalises the intelligence cycle as a structural model of a concrete strategic decision: whether and how a public-sector organisation adopts and scales a new general-purpose technology.

The empirical setting is the adoption of artificial intelligence (AI) across government agencies in the six countries of the Gulf Cooperation Council (GCC). This setting is well suited to a CI capability study for three reasons. First, technology adoption in government is a high-stakes strategic decision in which agencies must scan a fast-moving environment, weigh contested evidence, and commit scarce resources, which is the work an intelligence capability supports (Cavallo et al., 2021). Second, the public-sector context foregrounds intelligence governance, since AI deployment is shaped by explicit policy mandates, ethical guardrails, and data-protection rules that determine whether intelligence is translated into legitimate action (Wirtz et al., 2022). Third, the strategic objective behind AI adoption in the region, namely economic diversification and global competitiveness, makes sustainable competitive advantage an organisational rather than a purely commercial goal (Adomako & Tran, 2022; Medeiros & Maçada, 2022). Read together, AI adoption in this setting is a strategic technology-adoption decision that an organisational intelligence capability is meant to inform.

The research problem is therefore not whether organisations like AI, but whether the intelligence capability behind a technology-adoption decision can be specified as distinct, reliable, and valid constructs, and whether those constructs explain and predict the strategic outcome of the decision. Three research questions follow. RQ1: can the intelligence cycle be operationalised as a reflective measurement model with adequate reliability and discriminant validity in an organisational setting? RQ2: which dimensions of the intelligence capability, namely the capacity to collect, the capacity to analyse, and the governance that oversees the cycle, drive the strategic outcome of the technology-adoption decision? RQ3: does the model hold across multiple organisational contexts and predict outcomes out of sample?

The study makes three contributions. Theoretically, it advances CI as a measurable dynamic capability by linking the intelligence cycle, intelligence governance, and decision intelligence to a validated structural model rather than to a discursive account (Munir et al., 2023; Verganti et al., 2020). Methodologically, it provides a transparent and reproducible operationalisation, estimated on open primary data from 203 officials across six countries, that resolves the small-sample, single-context, and weak-measurement limitations common in applied CI work. Practically, it offers governance-ready guidance on where an organisation should invest to convert its intelligence capability into strategic value. The remainder of the paper presents the theoretical framework, the method, the results and their discussion, and the final considerations.

2 THEORETICAL FRAMEWORK

2.1 Competitive Intelligence as an Organisational Capability

Competitive intelligence is most usefully understood not as a discrete task but as an organisational capability: a stable, resource-based ability to convert environmental signals into decisions that confer advantage (Cavallo et al., 2021; Medeiros & Maçada, 2022). The resource-based view holds that advantage is sustained when a capability is valuable, rare, and difficult to imitate, which directs attention to the organisational routines that produce intelligence rather than to isolated reports (Medeiros & Maçada, 2022). Recent CI scholarship establishes the structure of this activity as a managed, end-to-end process. Cavallo and colleagues show that CI connects the activities of collection, analysis, and dissemination to the firm's strategy-formulation process rather than treating them as isolated tasks (Cavallo et al., 2021). Ibrahim and colleagues demonstrate empirically that CI practices raise sustainable competitiveness and firm performance, positioning intelligence as a strategic capability rather than a support function (Ibrahim et al., 2025). Work on strategic-intelligence systems frames the capability as an architecture that converts environmental data into decision-ready knowledge (Aurelio et al., 2021). These accounts frame intelligence as a process with measurable inputs, throughputs, and outputs, which is the structure this study models empirically.

Dynamic-capability theory develops this further. In changing environments, advantage depends on an organisation's ability to sense, seize, and reconfigure in response to change, and an intelligence capability is the sensing and seizing mechanism through which that reconfiguration is informed (Munir et al., 2023; Verganti et al., 2020). Recent evidence links analytical and dynamic capabilities to innovation and to sustainable competitive advantage, and shows that these capabilities are built from lower-order routines and resource positions (Munir et al., 2023; Adomako & Tran, 2022; Medeiros & Maçada, 2022). An intelligence capability is therefore best modelled as a set of distinct but related dimensions rather than a single undifferentiated trait. Treating CI as a dynamic capability reframes intelligence work as the systematic



transformation of signals into strategic action and implies that the capability, and its effect on decisions, can and should be measured.

2.2 The Intelligence Cycle, Governance, and Strategic Foresight

The intelligence cycle is the organising model of CI practice. In its established form it moves from direction and collection, through analysis and production, to dissemination and decision, after which the resulting action redefines the next cycle (Cavallo et al., 2021). The output of one phase is the input of the next, and increasingly the analysis phase is supported by formal analytic methods that anticipate environmental moves (Sassi et al., 2022). Governance sits at the centre of the cycle: clear guidelines, ethical standards, and oversight determine whether intelligence becomes legitimate action, a concern now formalised in risk-and-guideline frameworks for the governance of AI (Wirtz et al., 2022). Governance is therefore not peripheral but central, and the value of widely available data depends on the analytical and governance routines that turn it into decision-ready insight rather than on access alone (Medeiros & Maçada, 2022).

Strategic foresight extends the cycle forward in time. Organisations that interpret weak signals and anticipate discontinuities tend to outperform those that merely react, and analytical and foresight-oriented capabilities have been linked to superior performance (Munir et al., 2023; Ångström et al., 2023). An anticipatory intelligence function exists to detect strategic threats and opportunities before they fully materialise, so that the organisation can act rather than absorb surprise. Foresight, governance, and the cycle together describe an intelligence capability that is anticipatory, governed, and decision-oriented, which is the conception this study operationalises.

2.3 Competitive Intelligence in Data-Rich Public Organisations

Applying CI to the public sector extends these ideas. Governments increasingly act as data-rich organisations that must scan a turbulent technological environment, and AI is a prominent object of such scanning, with its organisational value still contested and fast-moving (Collins et al., 2021; Madan & Ashok, 2023). Public-sector AI adoption is governed by explicit mandates, data-protection regimes, and ethical standards, which makes intelligence governance an observable construct rather than an abstract ideal (Wirtz et al., 2022; Misra et al., 2023). Empirical studies of AI assimilation and AI capability in government show that technical infrastructure, organisational readiness, and governance jointly shape adoption outcomes (Mikalef et al., 2022; Alshahrani et al., 2022), that managerial readiness and institutional pressures drive willingness to adopt (Uren & Edwards, 2023; Rodriguez Müller et al., 2025), and that the challenges of public-sector adoption call for empirical, capability-based models (Neumann et al., 2024). Models of governmental AI acceptance combine technological, organisational, and environmental factors and have been estimated with structural methods (Assaf et al., 2024), while business-intelligence systems have been shown to improve organisational outcomes (Yiu et al., 2021). In the GCC specifically, national AI strategies couple heavy infrastructure investment with top-down policy direction, aiming at national competitiveness and economic diversification (Albous & Anouze, 2025a). Read as competitive intelligence, this is a setting in which the capacity to collect, the capacity to analyse, and the governance of the cycle should jointly determine whether a technology-adoption decision creates strategic value.

2.4 Operationalising the Cycle: Constructs, Hypotheses, and Gap

The framework maps the intelligence cycle onto three capability dimensions and one strategic outcome, each measured by survey items appropriate to an organisational respondent. Technical infrastructure (TI) represents the collection and processing backbone of the capability, namely the data, compute, networks, and platforms that allow an agency to gather and handle signals at scale (Mikalef et al., 2022). Organisational readiness (OR) represents the analytical dimension, namely the skills, leadership commitment, and learning culture that turn collected signals into insight (Uren & Edwards, 2023; Chatterjee et al., 2021). Governance environment (GE) represents intelligence governance, namely the guidelines, ethical standards, and oversight that legitimate the use of intelligence (Wirtz et al., 2022). AI outcomes (AIO) represent the strategic result of the technology-adoption decision, namely improvements in service efficiency, citizen trust, and responsiveness aligned with the organisation's strategic goals (Tangi et al., 2025).

Three hypotheses follow from the cycle. H1: the collection backbone (TI) and governance (GE) build the organisation's analytical readiness (OR), since infrastructure and clear guidance are preconditions for



analytical capacity. H2: the three capability dimensions jointly explain the strategic outcome (AIO) of the adoption decision. H3: analytical readiness mediates the effect of infrastructure and governance on the outcome, reflecting the sequential logic of the cycle in which collection and governance act through analysis. The gap this study fills is the absence, in applied CI research, of a validated, multi-context measurement and structural model that expresses the intelligence cycle in these terms. Table 1 positions the study against the strands reviewed.

Table 1. Positioning of the present study within the competitive-intelligence literature

Strand	Typical treatment	This study
CI as capability [1], [2], [5]	Conceptual or narrative accounts of the process	Reflective measurement of capability dimensions
Intelligence cycle and governance [1], [12]	Descriptive process models	Cycle expressed as an estimated structural model
Strategic foresight and dynamic capabilities [4], [6], [8]	Theoretical argument for anticipation	Capability dimensions linked to a strategic outcome
Applied adoption studies [13], [16], [27]	Correlational, often single context	Multi-country organisational PLS-SEM with prediction

3 METHOD

3.1 Research Design

The study uses a quantitative, model-based design that expresses the intelligence cycle as an estimable structure and tests it on organisational survey data. The design follows the competitive-intelligence operationalisation workflow in Figure 1, which mirrors the cycle: a strategic technology-adoption decision defines the intelligence need; primary survey data provide the collected signals; the capability dimensions are operationalised and assessed for reliability and validity; a structural model estimates how the dimensions drive the strategic outcome; predictive relevance is checked out of sample; and the results are read as governance-ready decision support. Estimation uses partial least squares structural equation modelling (PLS-SEM), which is appropriate for a prediction-oriented capability model with several related constructs (Hair & Alamer, 2022).

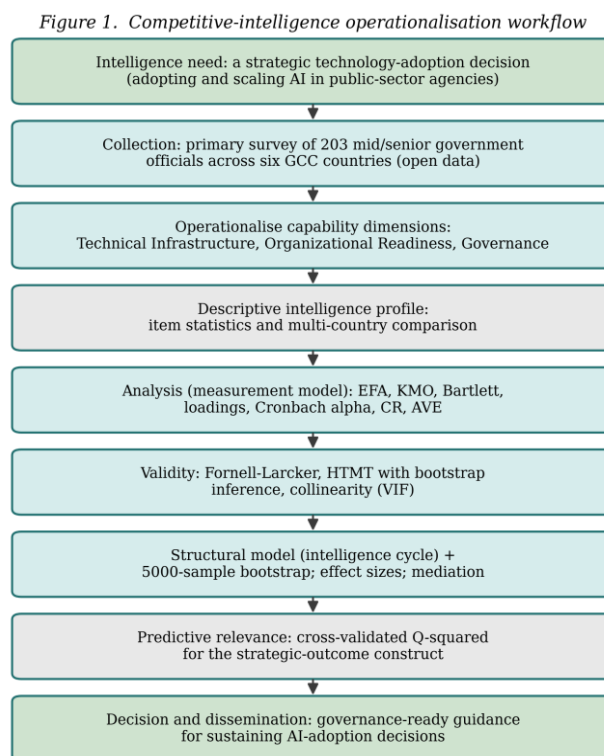


Figure 1. Competitive-intelligence operationalisation workflow, mapping the intelligence cycle onto the analytical steps of the study.

3.2 Data, Context, and Research Integrity

The analysis uses an openly available primary dataset of 203 valid responses from mid and senior officials in government agencies across the six GCC countries, distributed as United Arab Emirates 35, Kuwait 35, Saudi Arabia 34, Bahrain 34, Qatar 33, and Oman 32 (Albous & Anouze, 2025a). The instrument records eleven indicators on a five-point agreement scale covering technical infrastructure, organisational readiness, governance, and AI outcomes, together with the respondent's country. The sample is well suited to the research questions: it is organisational rather than educational, it spans six national contexts rather than one, and the respondents are decision-relevant officials rather than end users.

This is a secondary analysis of an open dataset, and the study makes no claim to have collected the data. The dataset and its documentation were produced by the original authors and are openly archived, the raw anonymised responses at <https://doi.org/10.7910/DVN/60PTXQ> and the cleaned dataset and codebook in the associated repository (Albous & Anouze, 2025a; Albous & Anouze, 2025b). Using an open, externally produced dataset strengthens reproducibility and removes the data-construction concerns that affect bespoke collections, since any reader can obtain the same records and reproduce every statistic reported here. The analysis, construct operationalisation, and structural model in this paper are the authors' own and are distinct from the index-construction purpose of the original release.

3.3 Constructs and Measurement Model

Four reflective constructs operationalise the capability. Technical infrastructure (TI) is measured by three items on reliable infrastructure, dedicated budget, and access to specialised platforms (the collection backbone). Organisational readiness (OR) is measured by three items on leadership championing, workforce skills, and a culture of experimentation (the analytical dimension). Governance environment (GE) is measured by two items on clear data and deployment guidelines and on adherence to legal and ethical standards (intelligence governance). AI outcomes (AIO) is measured by three items on service efficiency, citizen trust, and overall quality and responsiveness (the strategic decision outcome). Before modelling, factorability was confirmed: the Kaiser-Meyer-Olkin measure was 0.937 and Bartlett's test of sphericity was significant

(approximate chi-square = 2971.3, $p < 0.001$), both well within accepted thresholds for exploratory factor analysis.

3.4 Analytical Procedure

Indicators were standardised, after which the measurement and structural models were estimated together with PLS-SEM using a path-weighting inner scheme. The procedure follows the sequence in the algorithm below and uses the equations that follow it. Reliability and convergent validity were assessed through outer loadings, Cronbach's alpha, composite reliability, and average variance extracted (Hair & Alamer, 2022). Discriminant validity was assessed with the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT), the latter with a percentile bootstrap so that discriminant validity could be judged by inference rather than by a single point estimate (Roemer et al., 2021). Structural paths were estimated with a 5,000-sample bootstrap, effect sizes were summarised with the f-squared statistic, and predictive relevance was assessed with a cross-validated Q-squared for the strategic-outcome construct, complemented by a collinearity check and a parsimonious robustness model, following recent prediction-oriented guidance for PLS-SEM (Hair & Alamer, 2022; Sharma et al., 2023; Liengaard et al., 2021; Legate et al., 2023).

Algorithm 1. Estimation and validation procedure

```

01 input: 203 x 11 indicator matrix (TI, OR, GE, AIO) + country
02 standardise all indicators // Eq. (1)
03 factorability: KMO, Bartlett sphericity
04 PLS-SEM (Mode A, path weighting) -> outer weights, LV scores // Eq. (2)
05 measurement: loadings, alpha, CR, AVE // Eq. (4)
06 discriminant: Fornell-Larcker; HTMT + bootstrap CI // Eq. (5)
07 structural inner model: TI,GE -> OR ; TI,OR,GE -> AIO // Eq. (3)
08 bootstrap 5000: path CIs and p-values
09 effect sizes f2 ; collinearity VIF // Eq. (6)
10 mediation: indirect = a x b ; percentile bootstrap CI // Eq. (7)
11 predictive: 10-fold cross-validated Q2 for AIO // Eq. (6)
12 output: validated intelligence-cycle capability model

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The estimation rests on seven equations, each stated below with its parameters and meaning.

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \quad (1)$$

Equation (1) standardises the indicators, where x_{ij} is the raw score of respondent i on indicator j , $\bar{x}_j$ and s_j are that indicator's mean and standard deviation across the 203 respondents, and z_{ij} is the resulting standardised score. Standardisation places every indicator on a common scale so that loadings and path coefficients are directly comparable.

$$x_{ij} = \lambda_j \xi_{ik} + \varepsilon_{ij}, \quad \hat{\xi}_k = \sum_j w_j z_{ij} \quad (2)$$

Equation (2) is the reflective measurement model. Here ξ_i (the latent construct score) is reflected in each indicator through the outer loading λ_j , with measurement error ε_{ij} , and the construct score is formed as the weighted sum of standardised indicators using the outer weights w_j . This expresses each capability dimension (TI, OR, GE, AIO) through its own items.

$$\xi_m = \beta_0 + \sum_p \beta_{pm} \xi_p + \zeta_m \quad (3)$$

Equation (3) is the structural (inner) model, where ξ_m is an endogenous construct (organisational readiness or the AI outcome), ξ_p are its predictor constructs, β_{pm} are the structural path coefficients, β_0 is the intercept, and ζ_m is the structural error. This links the capability dimensions to one another and to the strategic outcome.

$$AVE = \frac{\sum_j \lambda_j^2}{J}, \quad \rho_c = \frac{(\sum_j \lambda_j)^2}{(\sum_j \lambda_j)^2 + \sum_j (1 - \lambda_j^2)} \quad (4)$$

Equation (4) defines convergent validity and reliability, where λ_j are the outer loadings and J is the number of indicators in a construct. The average variance extracted (AVE) is the mean share of indicator

variance captured by the construct, with 0.50 as the threshold, and composite reliability (ρ_c) measures internal consistency, with 0.70 as the threshold.

$$\text{HTMT}_{ab} = \frac{\bar{r}_{ab}}{\sqrt{\bar{r}_{aa}\bar{r}_{bb}}} \quad (5)$$

Equation (5) is the heterotrait-monotrait ratio (HTMT), where $\bar{r}_{ab}$ is the mean of the between-construct (heterotrait) indicator correlations and $\bar{r}_{aa}$ and $\bar{r}_{bb}$ are the mean within-construct (monotrait) correlations. A ratio whose bootstrap confidence interval excludes 1 indicates that constructs a and b are empirically distinct.

$$f^2 = \frac{R_{\text{incl}}^2 - R_{\text{excl}}^2}{1 - R_{\text{incl}}^2}, \quad Q^2 = 1 - \frac{\sum (y - \hat{y})^2}{\sum (y - \bar{y})^2} \quad (6)$$

Equation (6) gives the effect size and predictive relevance. The f-squared statistic compares the outcome variance explained with and without a given predictor (R-squared included versus excluded), with 0.02, 0.15, and 0.35 marking small, medium, and large effects; the cross-validated Q-squared compares observed scores y , predicted scores $\hat{y}$, and the mean $\bar{y}$, and a value above zero indicates genuine out-of-sample predictive relevance.

$$\text{Indirect} = a \times b, \quad \text{CI}_{95\%} \text{ by percentile bootstrap} \quad (7)$$

Equation (7) defines the mediation test, where a is the path from an antecedent to the mediator (organisational readiness) and b is the path from the mediator to the outcome; the indirect effect is the product a times b , judged significant when its percentile bootstrap confidence interval excludes zero.

4 RESULTS AND DISCUSSIONS

4.1 Descriptive Intelligence Profile

The eleven indicators show moderate-to-positive agreement, with construct item means between 3.18 and 3.68 on the five-point scale and standard deviations near 0.9 to 1.1, indicating real variation to model rather than ceiling effects. Outcome items (AIO) are rated highest and governance items (GE) lowest, a pattern consistent with a region that has invested heavily in infrastructure and visible results while still consolidating governance routines. Figure 3 reports construct means by country and shows that the four-part structure is stable across the six national contexts, which supports the multi-context claim and addresses external-validity concerns directly. Figure 4 shows the indicator correlation matrix, where items cohere strongly within their own construct.

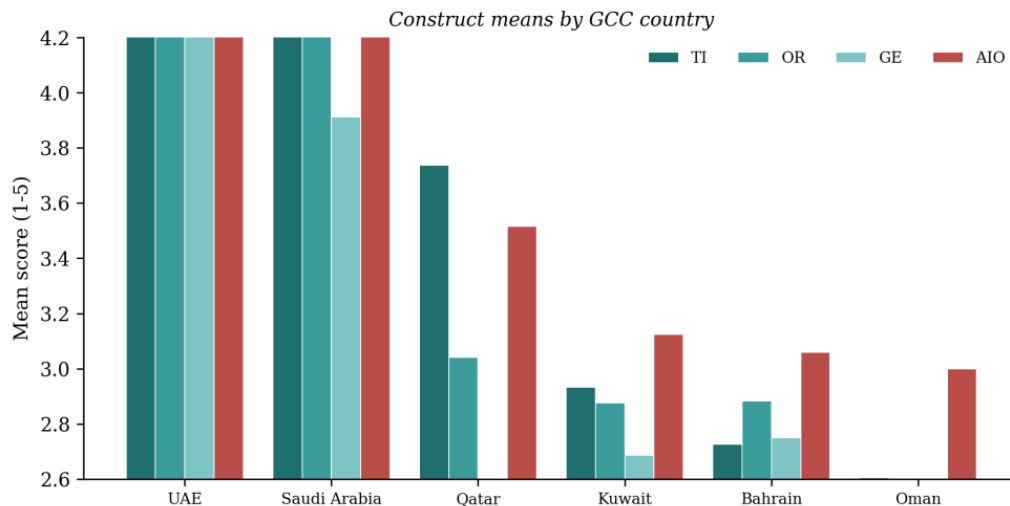


Figure 3. Construct mean scores by GCC country, showing a stable capability structure across six organisational contexts.

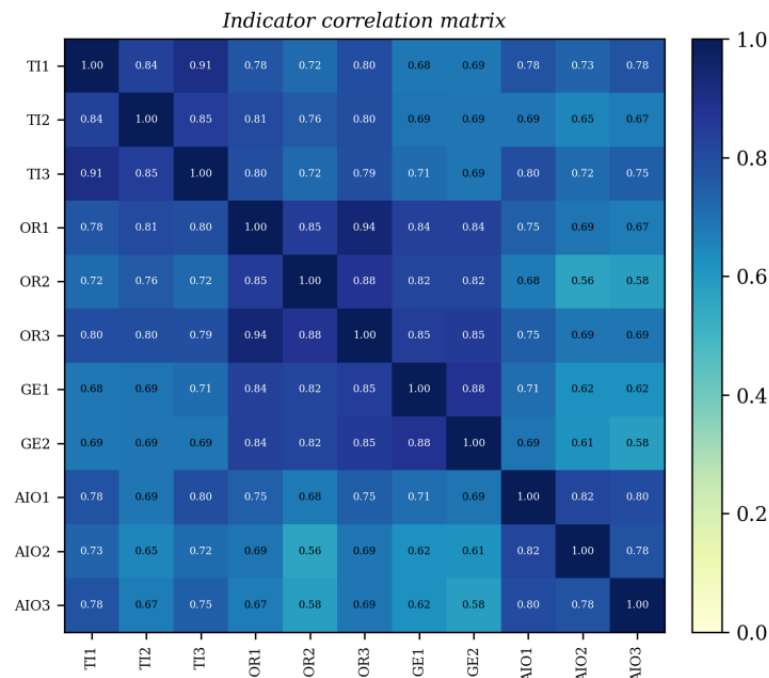


Figure 4. Indicator correlation matrix for the eleven measurement items.

4.2 Measurement Model: Reliability and Convergent Validity

The measurement model is strong and directly resolves the reliability concerns raised about earlier small-sample work. All outer loadings are high, from 0.923 to 0.977 (Table 2), and every construct exceeds the reliability and convergent-validity thresholds by a wide margin (Table 3). Cronbach's alpha ranges from 0.924 to 0.960, composite reliability from 0.952 to 0.974, and average variance extracted from 0.868 to 0.941, so each construct captures far more than the conventional half of its indicators' variance. The single-item limitation of earlier work is removed, since the strategic outcome (AIO) is now a three-item construct with an alpha of 0.924.

Table 2. Standardised outer loadings

Construct	Indicators	Loadings
TI	Infrastructure, budget, platforms	0.960, 0.936, 0.963
OR	Leadership, skills, learning culture	0.968, 0.942, 0.977
GE	Guidelines, legal and ethical adherence	0.970, 0.970
AIO	Efficiency, citizen trust, quality	0.942, 0.929, 0.923

Table 3. Construct reliability and average variance extracted

Construct	Items	Cronbach alpha	CR	AVE
TI	3	0.949	0.967	0.908
OR	3	0.960	0.974	0.927
GE	2	0.937	0.970	0.941
AIO	3	0.924	0.952	0.868



4.3 Discriminant Validity

Discriminant validity is assessed by two criteria and is supported. Under the Fornell-Larcker criterion the square root of each construct's AVE exceeds its correlations with the other constructs for every pair (Table 4). Under the more demanding HTMT criterion every ratio is below unity, a clear improvement on prior work where two ratios exceeded one, and the bootstrap inference is decisive: the upper bound of the 95 percent confidence interval is below 1.0 for all six pairs (Table 5). The highest ratio is between organisational readiness and governance (0.944, interval 0.916 to 0.968), which reflects the genuine institutional coupling of readiness and governance in centralised public administration, where the same top-down mandates that build analytical capacity also set the governance rules. Because every interval excludes one, discriminant validity holds by the inference criterion, and the readiness-governance overlap is carried forward as an interpreted feature rather than a measurement failure.

Table 4. Fornell-Larcker matrix (square root of AVE on the diagonal)

	TI	OR	GE	AIO
TI	0.953			
OR	0.844	0.963		
GE	0.749	0.895	0.970	
AIO	0.823	0.754	0.711	0.932

Table 5. HTMT ratios with 95 percent bootstrap confidence intervals

Construct pair	HTMT	95% CI	Discriminant validity
TI - OR	0.884	[0.845, 0.917]	Supported (CI < 1)
TI - GE	0.794	[0.727, 0.852]	Supported
TI - AIO	0.877	[0.825, 0.925]	Supported (CI < 1)
OR - GE	0.944	[0.916, 0.968]	Supported by inference (CI < 1)
OR - AIO	0.797	[0.733, 0.854]	Supported
GE - AIO	0.762	[0.688, 0.828]	Supported

4.4 Structural Model: The Empirical Intelligence Cycle

Figure 2 depicts the estimated model and Table 6 reports the coefficients, each bootstrapped over 5,000 resamples. The capability dimensions explain a large share of variance in both endogenous constructs: 87 percent of organisational readiness and 70 percent of the strategic AI outcome, the latter replicating the explanatory power reported for the original index. The collection backbone and governance jointly build analytical readiness, with both paths strong and significant (TI to OR beta = 0.395; GE to OR beta = 0.599). For the strategic outcome, technical infrastructure is the dominant driver (beta = 0.656, $p < 0.001$) and governance contributes significantly (beta = 0.205, $p = 0.044$), whereas organisational readiness has no direct effect once infrastructure and governance are accounted for (beta = 0.016, $p = 0.905$). H1 is supported, H2 is supported for infrastructure and governance, and the readiness path is not supported as a direct driver.

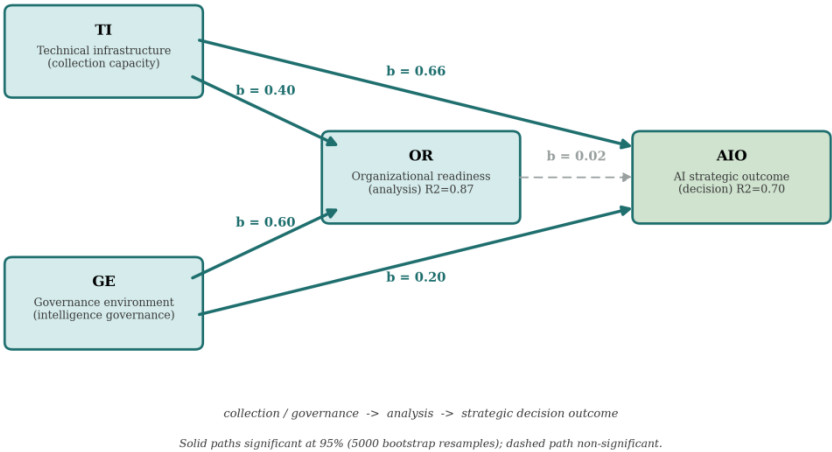


Figure 2. Estimated structural model as the empirical intelligence cycle (collection and governance, through analysis, to the strategic decision outcome). Solid arrows denote paths whose bootstrap 95 percent confidence interval excludes zero.

Table 6. Structural path coefficients (5,000 bootstrap resamples)

Path	beta	95% CI	p
TI -> OR	0.395	[0.323, 0.467]	< 0.001
GE -> OR	0.599	[0.529, 0.667]	< 0.001
TI -> AIO	0.656	[0.493, 0.823]	< 0.001
OR -> AIO	0.016	[-0.275, 0.292]	0.905
GE -> AIO	0.205	[0.006, 0.410]	0.044

4.5 Mediation: Is Analysis the Mechanism?

The cycle's sequential logic (H3) predicts that analytical readiness mediates the effect of infrastructure and governance on the outcome. The percentile bootstrap does not support mediation: the indirect effect of infrastructure through readiness is 0.006 (95 percent CI [-0.115, 0.112]) and of governance through readiness is 0.010 (95 percent CI [-0.159, 0.180]), both with intervals that include zero. The reason is structural rather than statistical: readiness is strongly produced by infrastructure and governance, but it does not itself convert into the strategic outcome once those two dimensions are present. In this high-mandate setting the capability translates into value directly through its collection backbone and its governance, with readiness acting as a built-up condition rather than an independent lever.

4.6 Collinearity and a Parsimonious Robustness Model

Collinearity diagnostics explain and bound the readiness result. In the full outcome model the variance inflation factors are 3.48 for infrastructure, 7.71 for readiness, and 5.05 for governance, so readiness and governance are partly collinear, consistent with their high HTMT. A parsimonious robustness model that retains only the two significant drivers (infrastructure and governance) is well identified, with both variance inflation factors at 2.28, and reproduces the explanatory power almost exactly (infrastructure beta = 0.66, governance beta = 0.21, R-squared = 0.695). The substantive conclusion is therefore stable: the strategic outcome of the technology-adoption decision is driven by the collection backbone and by governance, and this holds whether or not the collinear readiness path is included.



4.7 Effect Sizes and Predictive Relevance

Effect sizes confirm the hierarchy among drivers. The f-squared values on the outcome are 0.410 for technical infrastructure (a large effect), 0.027 for governance (a small but genuine effect), and effectively zero for readiness, matching the path results. Predictive relevance is strong: a ten-fold cross-validated Q-squared for the strategic-outcome construct is 0.682, well above zero, which indicates that the capability model predicts the outcome for officials not used in estimation and not merely fits the sample. Together these results show a capability model that is explanatory, parsimonious, and predictive without relying on opaque machine-learning machinery.

4.8 Discussion: Decision Intelligence, Governance, and Sustainable Advantage

Read as competitive intelligence, the model gives empirical content to the intelligence cycle and yields a clear strategic reading rather than a list of coefficients. The collection backbone, the technical infrastructure that lets an organisation gather and process signals at scale, is the principal source of strategic value in the technology-adoption decision, and governance is the second source, the dimension that legitimates intelligence and converts it into sanctioned action. Analytical readiness matters, but as a capacity that infrastructure and governance build rather than as an independent driver in this centralised context. This is a decision-intelligence result: it tells an organisation that, to sustain a technology-adoption decision, it should invest first in its collection and processing backbone and in the governance that authorises action, and treat readiness as a capacity to cultivate alongside them.

These findings speak to CI theory and practice. They represent an intelligence capability as a measurable dynamic capability whose dimensions are reliable, valid, and distinct, and they locate the source of sustainable advantage in the governed collection-and-analysis routines that the resource-based and dynamic-capability traditions emphasise (Adomako & Tran, 2022; Medeiros & Maçada, 2022), consistent with evidence that competitive intelligence raises sustainable competitiveness and performance (Ibrahim et al., 2025). They also give intelligence governance an empirical role: governance is not a compliance overlay but a direct contributor to the strategic outcome, consistent with frameworks that place governance at the centre of the intelligence and AI cycle (Wirtz et al., 2022). Finally, the multi-country result addresses external validity, since the same capability structure holds across six organisational contexts, and the strong cross-validated prediction supports the foresight claim that a governed intelligence capability anticipates outcomes rather than merely describing them (Munir et al., 2023; Ångström et al., 2023), with trustworthy AI-assisted decision-making as a condition for putting that intelligence to use (Vereschak et al., 2021).

5 FINAL CONSIDERATIONS

This study set out to move competitive intelligence from a discursive treatment to an empirically validated capability. It operationalised the intelligence cycle as a reflective structural model and estimated it on open primary data from 203 officials across the six GCC countries. The measurement model is reliable and valid, discriminant validity holds under the HTMT inference criterion, and the structural model explains 70 percent of the variance in the strategic outcome of a technology-adoption decision with strong out-of-sample prediction. Substantively, the collection backbone and governance are the drivers of strategic value, while analytical readiness is a condition that those dimensions build. The theoretical contribution is to represent competitive intelligence as a measurable dynamic capability; the methodological contribution is a transparent, reproducible operationalisation on open multi-context data; and the practical contribution is governance-ready guidance on where to invest to sustain a technology-adoption decision.

Three limitations frame the contribution and point to future work. First, the design is cross-sectional, so the cycle's temporal dynamics, in which one cycle's output becomes the next cycle's input, are inferred rather than observed; longitudinal or panel data would let the feedback loop be tested directly. Second, organisational readiness and governance are empirically coupled in this centralised setting, which elevates their shared variance; replication in more decentralised organisations, or a formative treatment of governance, would clarify whether the coupling is contextual or general. Third, the empirical setting is public-sector AI adoption, and although the capability constructs are defined at the level of the intelligence cycle rather than at the level of any one setting, which is what makes the model portable, re-estimating it on competitive-intelligence-native data from private firms would convert this validated demonstration into a cross-sector



account. These are extensions of a validated model rather than repairs to a fragile one, and the openly archived data make each of them directly reproducible.

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