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Technical University of Košice
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The BEHEALTH Intelligent Mentoring Tool for Quality Improvement in Nursing Education: A Pilot Demonstration

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Kristína Zgodavová, Peter Bober, Aleš Bourek, Juliana Gabzdilová,
Jozef Babečka

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ABSTRACT

Purpose: The purpose of this paper is to introduce the BEHEALTH Intelligent Mentoring Tool (IMT) and demonstrate its operational feasibility and analytical functionality as a practical decision-support tool for Institution Quality Managers (IQMs) in Nursing Vocational Education and Training (NVET) and Nursing Work-based Learning (NWBL).

Methodology/Approach: Rooted in the ENQA ESG (2015) and EQAVET framework (Council of the European Union, 2020), the IMT extends quality assessment by incorporating student mental health and well-being, occupational health and safety, and environmental management. A 360-degree survey on a 1–5 scale gathered pilot data from four stakeholder groups: managers, teachers, students, and employers across six European countries.

Findings: The pilot testing demonstrated the IMT's operational feasibility as a decision-support tool for IQMs. The IMT integrated multi-stakeholder assessments, identified perceptual gaps, and generated rule-based feedback to support institutional quality improvement.

Research Limitation/Implications: The survey data are intended to demonstrate IMT functionality and should not be used to draw generalisable conclusions.

Originality/Value of paper: The paper combines stakeholders' psychological mental health and well-being metrics with an automated prescriptive expert system for direct institutional action.

Keywords: nursing education; quality assurance; 360-degree assessment; intelligent mentoring tool.

Category: Research paper

Research Areas: Quality of Life; Strategic Quality Management

1 INTRODUCTION

Providing high-quality Nursing Vocational Education and Training (NVET) is a fundamental pillar of resilient healthcare systems. Unlike general educational pathways, NVET exhibits a unique duality, seamlessly blending theoretical classroom instruction with intensive work-based learning (WBL) in clinical environments. This dual nature introduces multi-layered operational risks and quality-assurance challenges. The clinical setting exposes nursing students not only to professional rigour but also to significant psychosocial stressors, occupational hazards, and complex environmental protocols. Consequently, traditional quality management frameworks that focus solely on academic compliance or administrative metrics are no longer sufficient to address the modern holistic needs of healthcare education.

In the era of Quality 5.0, the paradigm of quality assurance must transition from rigid, technocentric automation in Quality 4.0 toward human-centric, resilient, and sustainable ecosystems (Hashim, Tlemsani, Mason-Jones, Matthews, & Ndrecaj, 2024), where:

- Co-creation means involving students, teachers and administration not as passive objects of evaluation, but as active creators of quality processes.
- Well-being and mental health mean expanding quality indicators to include assessments of the psychological and cognitive well-being of students and staff (building resilience and preventing burnout).
- Reducing bureaucracy means digitising and streamlining processes so that data collection does not burden teachers with excessive administrative duties.

In the context of the Erasmus+ BEHEALTH project No: 2024-1-SK01-KA220-VET-000253130 “Promoting Quality Assurance in Nursing VET Education”, accessible at <https://behealthproject.eu/>, this implies that quality mentoring and monitoring must systematically incorporate dimensions such as student mental health, occupational health and safety, and institutional environmental management. Ensuring clinical competence cannot be decoupled from safeguarding the psychological well-being and physical safety of the trainees. To systematically operationalise these requirements, educational institutions and clinical providers require agile, data-driven evaluation frameworks. Current macro-level guidelines, specifically the European Standards and Guidelines for Quality Assurance in the European Higher Education Area (ENQA ESG, 2015) and the European Quality Assurance in Vocational Education and Training (EQAVET framework, Council of the European Union, 2020) directives, provide excellent structural foundations. However, they lack localised, granular tools capable of capturing the diverging perspectives of the diverse stakeholders involved in the NVET and NWBL ecosystem.

Quality in nursing education and training is perceived differently by four stakeholder groups: Managers (study programme guarantors; MA), teachers (TE), students (ST), and employers (EM).

To address this gap, this paper introduces the BEHEALTH Intelligent Mentoring Tool (IMT), the web-based tool developed within the Erasmus+ BEHEALTH project. The primary objective of the IMT is to monitor the comprehensive status of the internal quality assurance system within the institution. The tool digitises and extends the ten core areas of the ENQA ESG standards by embedding dedicated modules for Student Mental Health, Occupational Health and Safety, and Environmental Management. Utilising a rigorous 360-degree self-assessment methodology on a 5-point Likert scale, the tool aggregates evaluations from all four key stakeholder groups across six European countries: Slovakia, Hungary, Cyprus, Türkiye, Greece and Ireland.

The core scientific contribution of this study lies in demonstrating how the IMT utilises built-in expert intelligence to automatically translate stakeholder groups' feedback, visualised via multi-axial radar charts, into actionable institutional intelligence. For standards areas showing critical perceptual variance or low scores, the system generates automated qualitative recommendations to streamline the development of targeted institutional action plans. Conversely, high achievement combined with strong stakeholder alignment provides a basis for identifying good practices and supporting institutional and international comparison.

The primary objective of this study is to demonstrate the IMT as a practical decision-support tool for the IQM. The pilot data illustrate its multi-stakeholder assessment, aggregation, visualisation via multi-axial radar charts, perceptual-gap identification, and rule-based feedback. For standards areas showing critical perceptual variance or low scores, the system generates automated qualitative recommendations to streamline the development of targeted institutional action plans. The results should be interpreted as demonstrative IMT outputs rather than final assessments of NVET or NWBL quality.

2 LITERATURE REVIEW

2.1 Macro-Level Quality Frameworks: ENQA ESG Standards and EQAVET Directives in Vocational Contexts

The European landscape of quality assurance in education is governed by dual macro-level frameworks designed to harmonise standards, enhance transparency, and facilitate cross-border mobility. For higher education institutions, the Standards and Guidelines for Quality Assurance in the European Higher Education Area (ENQA ESG, 2015) serve as a key reference framework. The ENQA ESG framework structures internal and external quality assurance across ten core areas, emphasising student-centred learning, robust institutional governance, and

continuous data monitoring (Manatos, Sarrico, & Rosa, 2017). Concurrently, for vocational pathways, the European Quality Assurance in Vocational Education and Training EQAVET framework (Council of the European Union, 2020) provides a systematic, cyclical model comprising four key phases: planning, implementation, evaluation, and review. For work-based learning pathway e.g. hospitals or other institutions providing practical training usually (ISO 9001:2015) or (ISO 21001:2025) is applied. While both frameworks successfully standardise administrative compliance, their deployment in specialised practical domains reveals operational limitations. Recent literature highlights that generic quality indicators often fail to capture the specific micro-level risks inherent to clinical training and nursing work-based learning (NWBL) (Grollmann, Hugo, Thomas, & Wittig, 2021; Attenborough, Abbott, Brook, & Knight, 2019). In nursing education, where academic instruction is strictly intertwined with immediate clinical accountability, a structural misalignment frequently emerges between institutional quality policies and the real-world conditions experienced by trainees in healthcare facilities (Spector et al., 2020).

2.2 The Triad of Human-Centred Quality Assurance: Mental Health, Occupational Health and Safety, and Environmental Management

To bridge this gap, contemporary educational research increasingly advocates expanding quality metrics to encompass socio-environmental and psychological dimensions (Rathnayaka Mudiyansele, & Samita, 2026). The integration of student mental health, occupational health and safety, and environmental management into standards represents a crucial paradigm shift:

- **Student Mental Health:** Nursing trainees face unprecedented levels of psychological distress, clinical anxiety, and burnout due to early exposure to patient suffering, rotating shifts, and high-stakes clinical environments (Andargeery et al., 2025). Traditional quality frameworks treat student satisfaction as an administrative metric; however, modern Quality 5.0 principles dictate that psychological well-being is a direct prerequisite for learning efficacy and clinical safety (Leblebici, Saylam, & Özacit, 2026).
- **Occupational Health and Safety:** The clinical NWBL environment exposes students to biological hazards, sharps injuries, and ergonomic strain. Rigorous OHS protocols within the educational quality loop reduce institutional liability and protect the workforce pipeline (Alsharari & Kerari, 2024).
- **Environmental Management:** Modern healthcare facilities operate under strict green directives, waste segregation protocols, and eco-efficiency standards. Integrating environmental management into nursing training ensures that future professionals comply with sustainability mandates, a dimension explicitly emphasised in the updated European green transition priorities. The synchronisation of these three pillars with standard ENQA ESG standards ensures that quality monitoring transitions from superficial bureaucratic auditing, e.g. in hospitals or periodic programme reviews in

education institutions, to a holistic evaluation of institutional and environmental resilience (Lattanzio et al., 2022).

2.3 The 360-Degree Evaluation and the Perceptual Gap in Quality Assurance

A major failure mode in traditional quality assurance systems is the reliance on single-source feedback, typically gathered through isolated student evaluations or top-down managerial monitoring or auditing. Such approaches mask internal operational friction. Methodologically, a 360-degree feedback mechanism solves this bottleneck by collecting simultaneous evaluations from four key stakeholder groups (Morgan, Cannan, & Cullinane, 2005). In organisational theory, comparing these distinct vectors regularly reveals a significant “perceptual gap”. Managers (study program guarantors) often perceive quality through the lens of policy compliance and resource allocation. Teachers focus on pedagogical delivery and curriculum adherence. Students evaluate quality based on real-time subjective experience and stress levels, while employers assess trainees’ immediate technical competence and readiness.

2.4 Digital Transformation and Expert Systems: Driving Quality 5.0

The volume of multi-dimensional data generated by a 360-degree multi-national survey requires advanced analytical processing to remain actionable for decision-makers. In the Quality 5.0 framework, digital transformation must move beyond descriptive data storage (e.g., merely displaying tables of means) toward prescriptive analytics driven by expert systems (Leblebici et al., 2026).

3 METHODOLOGY

3.1 IMT Operational Workflow

The IMT is designed to support the Institution Quality Manager (IQM) in continuously improving the institution’s Internal Quality Assurance System (IQAS). To initiate the assessment process, the IQM registers the institution in the IMT and establishes a respondent pool representing the four stakeholder groups: managers (study programme guarantors; MA), teachers (TE), students (ST), and employers (EM). The IQM provides the participating respondents with the necessary instructions and invites them to complete the 360-degree survey independently through the web-based IMT.

Following completion of the data-collection phase, the IMT processes and aggregates the responses and provides the IQM with quantitative and visual outputs at different levels of aggregation. These outputs enable the IQM to examine the assessment results by criterion and stakeholder group, compare stakeholder perspectives, and identify areas of alignment and perceptual gaps. The

results are presented numerically and through multi-axial radar charts, allowing the institution's quality performance to be examined from multiple perspectives.

In addition to quantitative and visual analytics, the IMT applies built-in rule-based expert intelligence to generate targeted institutional feedback. Depending on the achievement level and the degree of alignment among stakeholder-group assessments, the system provides qualitative feedback and recommendations through the Remediation Loop or the Excellence Loop. The Remediation Loop supports the identification of areas requiring improvement and proposes corresponding corrective or developmental actions, whereas the Excellence Loop identifies areas of high achievement and supports the maintenance and further development.

The overall operational workflow of the IMT and its integration into the institutional quality assurance cycle are illustrated in Figure 1.

The combined quantitative, visual, and qualitative outputs provide the IQM with decision-support information for identifying improvement priorities and developing an institutional action plan. The implementation and monitoring of the resulting action plan remain the responsibility of the institution. In this way, the IMT functions as a decision-support component of the IQAS, facilitating a continuous cycle of stakeholder assessment, evidence-based evaluation, targeted improvement, and quality development.

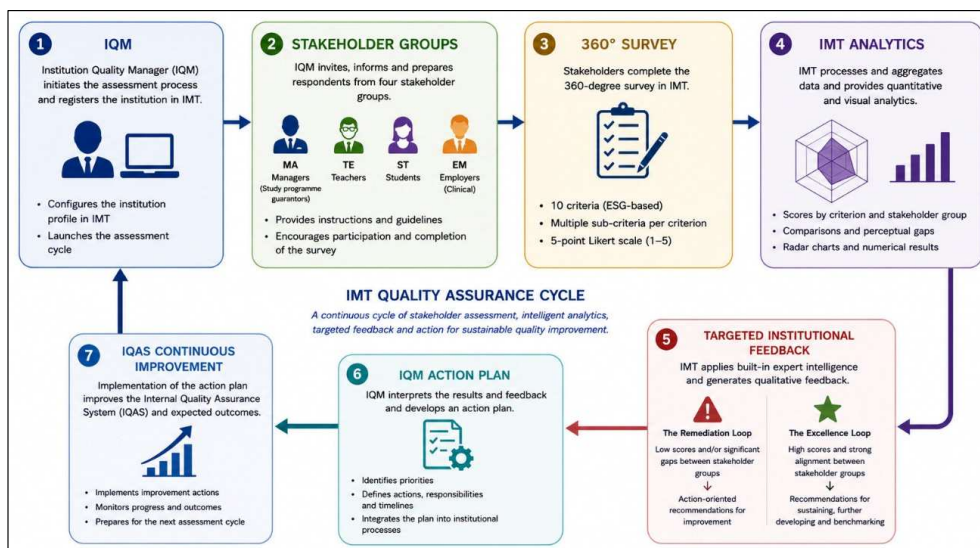


Figure 1 – The overall operational workflow of the IMT and its integration into the institutional quality assurance cycle

Repeated assessment cycles allow the IQM to monitor changes in institutional quality performance over time and to evaluate the effects of previously implemented improvement actions.

3.2 Pilot Demonstration Design and Evaluation Framework

This study adopts a pilot demonstration design aimed at evaluating the operational feasibility and analytical functionality of the IMT in real NVET and NWBL settings. The multinational implementation provides diverse institutional and stakeholder contexts in which the complete IMT workflow can be demonstrated. The study is therefore primarily demonstrative and exploratory rather than confirmatory or comparative. The methodological framework implemented in the IMT integrates the four-phase EQAVET framework (Council of the European Union, 2020) quality cycle (Planning, Implementation, Evaluation, and Review), the ten internal quality assurance standards of the ENQA ESG (2015), and the global guidelines of the World Federation for Medical Education (WFME, 2011).

The core research focus expands these standard administrative vectors by embedding non-traditional micro-level compliance areas directly relevant to work-based learning environments. Specifically, the methodology investigates how traditional educational quality co-exists with student mental health resources, occupational health and safety, and institutional environmental hygiene and sustainability protocols (Djukic et al., 2013).

3.3 360-degree Tool and Survey Structure

The data collection instrument consists of a multi-perspective, 360-degree survey designed for four stakeholder groups:

- Managers (study programme guarantors; MA): Providing perspectives on programme governance, evaluation, development, and compliance with accreditation requirements.
- Teachers (TE): Providing pedagogical, evaluative, and clinical supervision perspectives.
- Students (ST): Providing perspectives on educational experience, workload, and psychological well-being.
- Employers (EM): Assessing competencies, workforce readiness, and compliance with healthcare delivery requirements.

The survey evaluates ten quality assurance areas derived from the ENQA ESG (2015). For the purposes of the IMT survey, these ENQA ESG areas are referred to as criteria. Each criterion is assessed through a set of statements, referred to as sub-criteria in the IMT. The sub-criteria are formulated based on the respective ENQA ESG requirements and are complemented by project-specific statements addressing dimensions particularly relevant to NVET and NWBL, including student mental health and well-being, occupational health and safety (OHS), and environmental management. For example, Criterion 1 (Policy for Quality Assurance) includes project-specific sub-criteria addressing safe and secure NWBL environments and environmentally sustainable infrastructure. Similarly, Criterion 2 (Design and Approval of Programmes) includes additional sub-criteria

addressing OHS, environmental hygiene and waste management, mental and physical health, stress reduction, and counselling resources.

All sub-criteria are rated on a 5-point Likert scale (Allen & Seaman, 2007), corresponding to the following achievement levels: 1 – Minimal Achievement, 2 – Developing Achievement, 3 – Moderate Achievement, 4 – High Achievement, and 5 – Full Achievement. The complete set of survey criteria and sub-criteria, including the project-specific statements, is available in a separate document published on the BEHEALTH project accessible at <https://behealthproject.eu/>.

The 360-degree tool was developed through expert discussions among the BEHEALTH project partners and validated during the beta testing by representatives of the NVET and NWBL institutions.

3.4 Data Collection and Multi-National Sampling Procedures

IMT pilot data were collected between March and July 2026 from participating NVET and NWBL institutions in six countries represented in the BEHEALTH project: Slovakia, Hungary, Cyprus, Türkiye, Greece, and Ireland. The study involved four stakeholder groups: managers, teachers, students, and employers. Each participating institution's IQM coordinated the assessment process.

The pilot sample was designed to provide real-world data to test and demonstrate the complete IMT workflow across different stakeholder, institutional, and national contexts. A total of 112 respondents from 14 NVET institutions and 14 NWBL institutions participated in the pilot testing.

Table 1 presents the distribution of participating institutions and respondents by country and stakeholder group. The sampling procedure targeted NVET and NWBL institutions with established, accredited Internal Quality Assurance Systems (IQAS) and authorisation to deliver nursing qualification programmes. Including both educational and clinical institutions, together with four stakeholder perspectives, enabled assessment of institutional performance across different institutional and national contexts.

Table 1 – Distribution of participating institutions and respondents by country and stakeholder group in the pilot study

Country	NVET institutions	NWBL institutions	Respondents	Managers	Teachers	Students	Employers
Slovakia	4	4	32	8	8	8	8
Hungary	2	2	16	4	4	4	4
Cyprus	2	2	16	4	4	4	4
Türkiye	2	2	16	4	4	4	4
Greece	2	2	16	4	4	4	4
Ireland	2	2	16	4	4	4	4
Total	14	14	112	28	28	28	28

The survey was fully digitalised and administered through the interactive, multilingual, web-based IMT, available on the BEHEALTH project website (<https://behealthproject.eu/intelligent-mentoring-tool/>). The processing of

personal data associated with access to and use of the IMT was conducted in accordance with applicable data protection legislation, including the General Data Protection Regulation (GDPR), as specified in the BEHEALTH project website's registration conditions.

3.5 IMT Data Processing and Analytics

The IMT processes survey data through a hierarchical workflow corresponding to the evaluation framework. Individual sub-criterion ratings are first aggregated into criterion-level scores and subsequently into stakeholder-group results, enabling comparison of MA, TE, ST, and EM within an institution. Further aggregation supports institutional and cross-country comparisons.

The criterion-level results are presented through numerical indicators and multi-axial radar charts. The simultaneous visualisation of the four stakeholder-group profiles enables differences in perceptions of quality among MA, TE, ST, and EM to be identified. These differences provide the basis for identifying perceptual gaps between stakeholder groups and for highlighting criteria in which stakeholder assessments are closely aligned or substantially divergent.

In the final processing stage, the IMT applies predefined rule-based logic to link the quantitative assessment results with qualitative feedback and management recommendations. Based on the calculated achievement levels and the degree of alignment among stakeholder-group assessments, the analytical workflow follows two complementary pathways:

- The Remediation Loop is activated when the assessment identifies areas of insufficient achievement or substantial differences between stakeholder-group perceptions. The IMT links the identified area to the corresponding content in its predefined knowledge base and generates qualitative recommendations to address the detected weaknesses. These recommendations support the IQM in identifying priorities and formulating targeted improvement actions.
- The Excellence Loop applies to areas demonstrating the highest level of achievement together with strong alignment among stakeholder-group assessments. Rather than generating corrective recommendations, the IMT provides feedback aimed at maintaining and further developing the achieved level of performance. Such results can also serve as a basis for identifying good practices and supporting institutional, national, or international comparison.

Through these two pathways, the IMT extends the survey from descriptive assessment towards rule-based decision support by linking stakeholder-group evaluations with targeted institutional feedback. The detailed calculation procedures, aggregation rules, achievement-level thresholds, and conditions used to activate the Remediation and Excellence Loops are described in Section 3.6.

3.6 Statistical Calculation Principles and Data Aggregation

The IMT data structure comprises eight dimensions: country, institution type (NVET or NWBL), institution, stakeholder group, criterion, sub-criterion, respondent, and assessment time. These dimensions enable the collected data to be aggregated and analysed from different perspectives.

For the purposes of the pilot implementation, the IMT applies a transparent equal-weight aggregation model. Each sub-criterion contributes equally to its corresponding criterion score, each criterion contributes equally to the overall stakeholder-group assessment, and each of the four stakeholder groups contributes equally to the institutional score. At country level, participating institutions represent the units of comparison and contribute equally to the aggregated score. Equal weighting was selected to ensure transparency and interpretability of the pilot decision-support model and should not be interpreted as an empirically validated optimal weighting scheme.

The calculations presented below describe the processing of data obtained within a single assessment cycle; therefore, the time dimension is held fixed and is not explicitly included in the following equations. Similarly, country and institution type are treated as fixed for the purpose of simplifying the mathematical notation. The same calculation procedure is applied independently to each institution and assessment cycle. The pilot study comprised a single assessment cycle; consequently, analyses of changes over time were not performed.

Step 1: Data Collection and Normalisation

Each respondent logged into the IMT belongs to some stakeholder group of the institution. When evaluating the survey items, the respondent assigns a raw score to each sub-criterion:

$$s_{ricj} \in \{1,2,3,4,5\}, \quad (1)$$

where $r \in R_{gj}$ is a respondent belonging to the set of respondents R_{gj} , g is the stakeholder group of institution j , and i is the sub-criterion of criterion c .

The following equation (2) linearly rescales the discrete ordinal data s_{ricj} from the 5-point Likert scale into a 0–100% value suitable for multi-axial radar charting:

$$X_{ricj} = \frac{s_{ricj}-1}{4} \cdot 100\%. \quad (2)$$

Step 2: Sub-criteria to Criterion Aggregation

Criterion-level score X_{rcj} of respondent $r \in R_{gj}$ for criterion c in institution j is:

$$X_{rcj} = \frac{1}{I_c} \sum_{i=1}^{I_c} X_{ricj}, \quad (3)$$

where I_c is the number of sub-criteria for criterion c .

Step 3: Respondents to stakeholder group aggregation

Average criterion score X_{gcj} of criterion c for group g in institution j is:

$$X_{gcj} = \frac{1}{N_{gj}} \sum_{r \in R_{gj}} X_{rcj}, \quad (4)$$

where $N_{gj} = |R_{gj}|$ is the number of respondents in group g in institution j .

Step 4: Perceptual Gap and Inter-Group Variance Analysis

The multi-axial radar charts plot the values of X_{gcj} for all four groups simultaneously across the criterion axes. To algorithmically identify areas of friction, the IMT calculates the Perceptual Gap Δ_{cj} for each criterion, defined as the maximum absolute difference between any two stakeholder groups:

$$\Delta_{cj} = \max(X_{gcj}) - \min(X_{gcj}); \text{ for } g \in \{1, 2, 3, 4\}. \quad (5)$$

Furthermore, to measure overall institutional misalignment within a specific standards area, the system computes the inter-group variance (σ_A^2):

$$\sigma_{cj}^2 = \frac{1}{4} \sum_{g=1}^4 (X_{gcj} - \mu_{cj})^2 \quad (6)$$

where μ_{cj} is the global institutional mean for X_{gcj} across all groups.

Step 5: Overall Institutional Assessment by Stakeholder Group

To obtain an overall assessment X_{gj} of institution j from the perspective of stakeholder group g , the criterion-level scores X_{gcj} are aggregated across all criteria:

$$X_{gj} = \frac{1}{C} \sum_{c=1}^C X_{gcj}, \quad (7)$$

where C is the number of evaluated criteria.

Step 6: Institution and Country Level Aggregation

The overall assessment score of institution j is calculated by averaging the overall scores X_{gj} across the four stakeholder groups:

$$X_j = \frac{1}{G} \sum_{g=1}^G X_{gj}, \quad (8)$$

where $G = 4$ is the number of stakeholder groups.

For cross-country comparison, institutions are grouped by country and institution type (NVET or NWBL). The country-level score for institution type k in country u is calculated as:

$$X_{ku} = \frac{1}{J_{ku}} \sum_{j \in J_{ku}} X_j, \quad (9)$$

where J_{ku} is the set of institutions of type k in country u , and $J_{ku} = |J_{ku}|$ is the number of these institutions. The resulting X_{ku} represents the average overall institutional score for the respective institution type and country.

Step 7: Detailed Verbal Feedback and Recommendations

The final phase of the prescriptive data processing pipeline within the IMT transforms quantitative scores into structured verbal feedback and operational management recommendations. A deterministic, rule-based decision-support mechanism produces recommendations by linking calculated achievement levels to predefined, criterion-specific feedback stored in the IMT knowledge base. The knowledge base was developed through expert discussions among the BEHEALTH project partners and validated by external institutions.

The platform's algorithm maps the final percentage score of each monitored quality criterion onto distinct qualitative performance tiers, automatically pairing them with dynamic action directives according to Table 2.

Table 2 – Criterion achievement levels, thresholds and recommendations

Achievement level	Threshold	Recommendation
Minimal	0 – 20%	The IQA mechanism is not established
Developing	21 – 40%	The IQA mechanism exists in a limited or informal capacity
Moderate	41 – 60%	The IQA system is working, but inconsistently
High	61 – 80%	The IQA system is well-established and regularly used
Full	81 – 100%	The feedback process is strategic, embedded, and part of a continuous improvement cycle

Lower achievement levels prioritise corrective and developmental actions, whereas high and full achievement levels focus on sustaining performance, further development, and national or international comparison. Examples of the generated feedback are presented in Section 4.2.

The Excellence Loop is activated when the assessment reaches the Full Achievement level (81–100%). For all other achievement levels, the IMT activates the Remediation Loop and provides recommendations aimed at addressing identified weaknesses and supporting further improvement. This automated apparatus ensures that the institutional quality manager transitions from passive data visualisation to immediate, text-guided institutional action, significantly optimising the formulation of targeted action plans.

4 PILOT DEMONSTRATION OF IMT FUNCTIONALITY

The pilot testing demonstrated the operational functionality of the IMT across the participating NVET and NWBL institutions. The following sections present the main analytical outputs available to respondents and IQMs, progressing from

individual and stakeholder-group assessment to institutional and cross-country comparisons.

4.1 Individual and Stakeholder-Group Assessment

The pilot testing demonstrated the ability of the IMT to present assessment results at both individual and stakeholder-group levels. For each respondent r , the criterion-level scores X_{rcj} are visualised in a multi-axial radar chart.

In the respondent view, the individual criterion-level profile X_{rcj} is displayed together with selectable stakeholder-group profiles X_{gcj} . Respondents can therefore compare their individual assessment with the aggregated assessment of all stakeholder groups.

The IQM view presents only the aggregated criterion-level profiles X_{gcj} for the four stakeholder groups, without displaying individual respondent scores. This enables the IQM to compare stakeholder perspectives across the evaluated criteria and identify areas of agreement or divergence.

Figure 2 illustrates these role-specific views using pilot data for one institution. The simultaneous presentation of stakeholder-group profiles provides a visual basis for identifying perceptual gaps, which are further quantified and interpreted in Section 4.3. The “Personal Actual” profile represents the assessment of an individual respondent, a manager in this example.

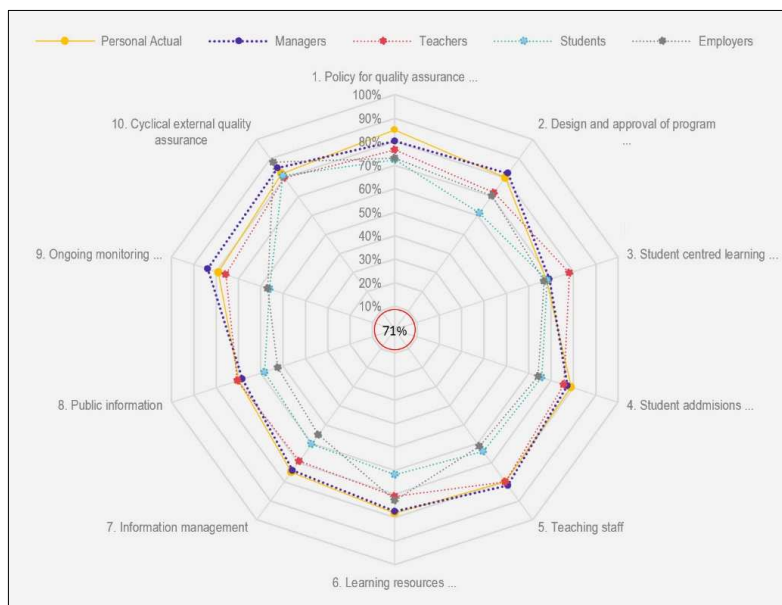


Figure 2 – Comparison of individual and stakeholder-group criterion scores within an institution

4.2 Automated Detailed Feedback and Recommendations

In addition to quantitative and visual results, the IMT provides qualitative feedback and targeted recommendations for the evaluated criteria. Based on the calculated achievement level, the built-in rule-based expert intelligence links the assessment result to predefined recommendations supporting either improvement through the Remediation Loop or further development through the Excellence Loop.

Figure 3 illustrates how quantitative assessment results are translated into practical decision-support information that can be used by the IQM when defining improvement priorities and developing an institutional action plan. In the pilot case presented, the three lowest-scoring criteria were Criterion 8 (62.4%), Criterion 7 (64.7%), and Criterion 9 (68.1%).

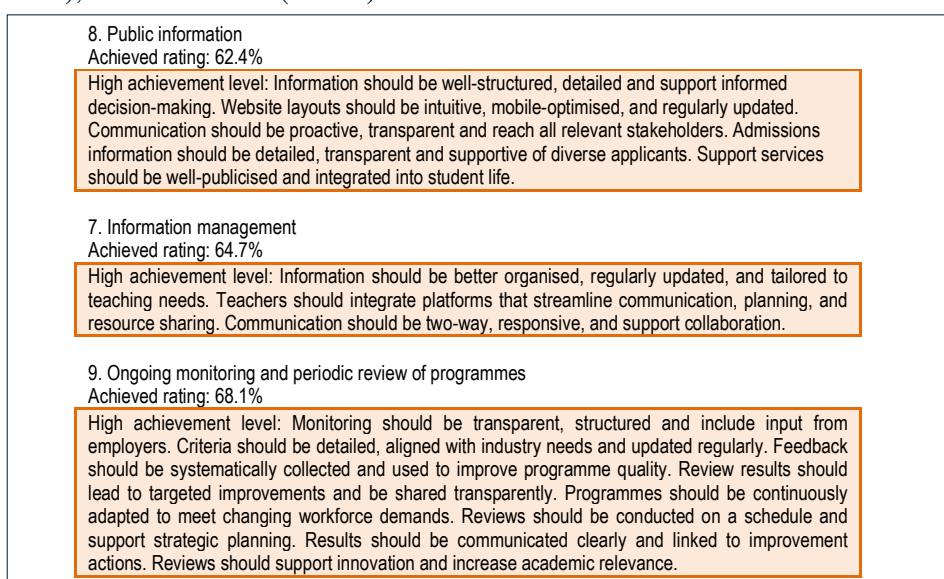


Figure 3 – Example of IMT-generated detailed feedback and recommendations for criteria with lowest scores

4.3 Identification and Interpretation of Perceptual Gaps

The pilot results revealed substantial differences between stakeholder-group assessments in several criteria (Figure 4). The largest Perceptual Gap was identified for Criterion 9 (Ongoing Monitoring), reaching 27.7 percentage points between managers (83.8%) and students (56.1%). Further notable gaps were observed for Criterion 2 (Design and Approval of Programmes), with a 20.9-point difference between managers (82.2%) and students (61.3%), and Criterion 5 (Teaching Staff), with a 20.5-point difference between managers (81.9%) and employers (61.4%).

Figure 4 ranks these differences and identifies the stakeholder groups defining each gap, enabling the IQM to identify priority areas for further investigation and targeted improvement.

Criterion (%)	Overall score (%)	Managers (%)	Teachers (%)	Students (%)	Employers (%)	Perceptual Gap (%)	Largest gap between
9. Ongoing monitoring ...	68.1	83.8	75.7	56.1	56.9	27.7	Managers - Students
2. Design and approval of program ...	71.5	82.2	72.0	61.3	70.4	20.9	Managers - Students
5. Teaching staff ...	71.9	81.9	80.1	64.0	61.4	20.5	Managers - Employers

Figure 4 – IMT identification and interpretation of highest perceptual gaps between stakeholder groups

4.4 Overall Institutional Assessment by Stakeholder Group

The overall stakeholder-group assessment further confirmed differences in perceptions of institutional quality. Managers reported the highest overall score (78.0%), followed by teachers (74.9%), while employers (66.1%) and students (64.9%) provided lower assessments. The overall institutional score was (71.0%), corresponding to the High Achievement level.

Figure 5 demonstrates that aggregation at the institutional level preserves the differences between stakeholder perspectives and provides the IQM with a concise overview of their relative assessments.

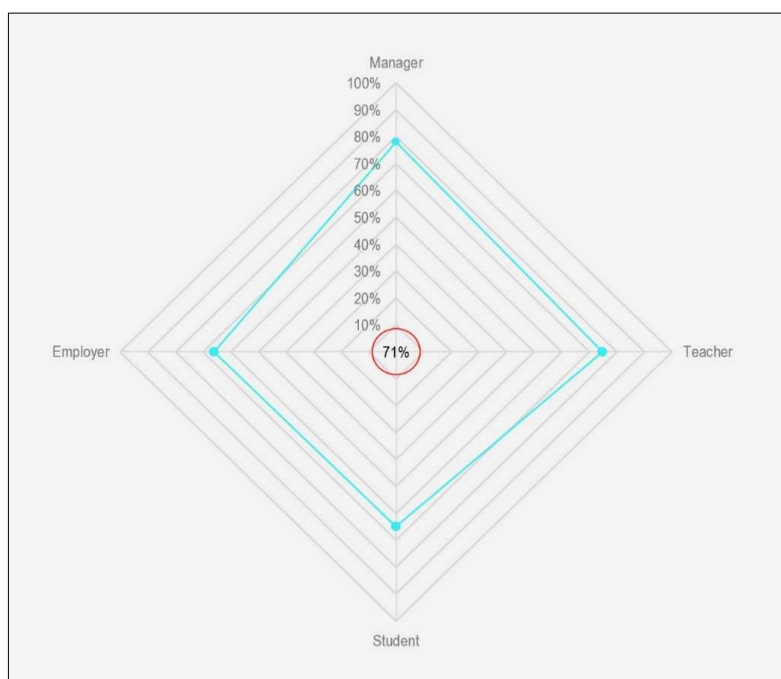


Figure 5 – Overall institutional assessment by stakeholder group

4.5 Cross-Country Institutional Comparison

Cross-country aggregation revealed differences in the pilot assessment results for both institution types. The mean country-level score was 76.5% for NVET institutions and 70.7% for NWBL institutions. Cyprus achieved the highest scores for both NVET (89%) and NWBL (85%), while Türkiye showed identical scores for the two institution types (79%). The largest within-country difference was observed in Greece, where the NVET score reached 80% compared with 62% for NWBL. Figure 6 demonstrates the potential of the IMT for comparing aggregated institutional performance across countries and between NVET and NWBL settings. Given the pilot nature of the sample, these results should be interpreted as illustrative comparisons.

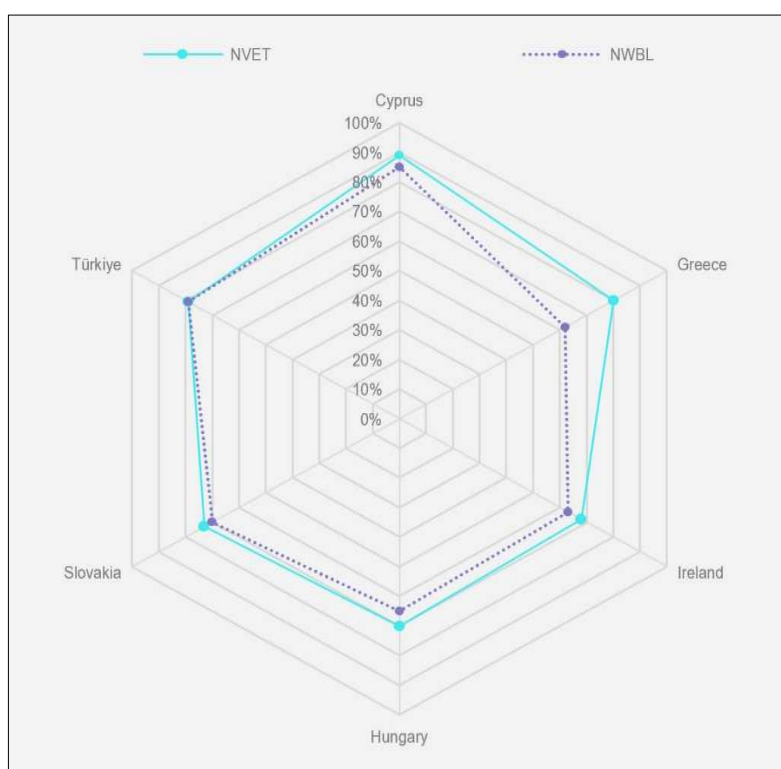


Figure 6 – Cross-country comparison of overall institutional scores for NVET and NWBL institutions

5 DISCUSSION

5.1 Multi-Stakeholder Assessment and the Perceptual Gap

The pilot results demonstrate the practical value of maintaining separate stakeholder perspectives within the 360-degree assessment. Although the overall institutional score in the presented case was (71.0%), stakeholder-group

assessments ranged from (64.9%) for students to (78.0%) for managers. At criterion level, these differences were even more pronounced, with the largest Perceptual Gap reaching 27.7 percentage points for Ongoing Monitoring (Figure 4). Aggregation into a single institutional score would therefore conceal potentially important differences in how quality is perceived by individual stakeholder groups.

The identification of perceptual gaps provides the IQM with information that cannot be obtained from overall mean scores alone. Divergent assessments may indicate differences between institutional policies, their implementation, and the actual experience of stakeholders. Conversely, close alignment among stakeholder groups strengthens the evidence that a quality criterion is consistently perceived across the institution. Thus, the multi-stakeholder approach extends IQAS evaluation beyond overall performance measurement.

5.2 From Assessment to Action: Rule-Based Decision Support

A key practical contribution of the IMT is its transition from descriptive assessment to rule-based decision support. Unlike a conventional online survey or dashboard that primarily collects and visualises data, the IMT links quantitative results to predefined qualitative feedback and targeted recommendations.

Through the Remediation and Excellence Loops, the IMT distinguishes between areas requiring improvement and those demonstrating high achievement. This provides the IQM with an interpretation of the assessment results and supports the identification of priorities for an institutional action plan. The IMT therefore does not replace managerial decision-making but provides structured evidence and expert-based guidance to support it.

5.3 Institutional Learning and Continuous Improvement

The aggregation of stakeholder assessments at institutional and country levels extends the use of the IMT beyond the evaluation of individual quality criteria. Institutional profiles and cross-country comparisons provide the IQM with reference information for identifying relative strengths, weaknesses, and opportunities for improvement.

These results can inform the institutional action plan and subsequent quality improvement activities. Repeated assessment cycles will further enable institutions to compare current and previous results, monitor changes in quality performance over time, and evaluate whether implemented actions have produced the expected improvements. In this way, the IMT supports the continuous quality improvement cycle illustrated in Figure 1.

5.4 Limitations and Future Development

The present study was based on pilot testing involving 112 respondents from 14 NVET and 14 NWBL institutions across six countries. Although the four

stakeholder groups were equally represented, the limited number of participating institutions and the higher representation of Slovakia restrict the generalisability of the findings. The country-level results should therefore be interpreted only as pilot comparisons. Further testing with larger samples is required to assess the reliability and validity of the evaluation framework and the comparability of results across institutional and national contexts. Monitoring of changes over time will require repeated assessment cycles.

The structure of the criteria and the survey questions is aligned with the specific requirements of the ENQA ESG (2015); therefore, any future revision of these standards will require corresponding updates to the 360-degree survey, while the IMT evaluation framework, including averaging, aggregation, and graphical visualisation, can remain unchanged.

6 CONCLUSION

The BEHEALTH Intelligent Mentoring Tool (IMT) provides a digital, multi-stakeholder approach to supporting internal quality assurance in NVET and NWBL institutions. By integrating ENQA ESG-based criteria with student mental health and well-being, occupational health and safety, and environmental management, the IMT extends quality assessment beyond conventional administrative indicators.

Pilot testing demonstrated that the IMT can preserve and visualise stakeholder differences that may be obscured by institutional averages. The largest criterion-level Perceptual Gap reached 27.7 percentage points, while the overall institutional assessment showed higher scores from managers and teachers than from students and employers. The IMT further links quantitative results to targeted qualitative feedback and enables institutional and cross-country comparisons.

By combining multi-stakeholder assessment, perceptual-gap analysis, rule-based feedback, and cross-institutions comparison, the IMT provides the IQM with structured decision support for evidence-based quality improvement.

Country-level results from the present pilot should be regarded as illustrative. Broader and repeated deployment is required to validate comparative applications and assess changes over time.

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ABOUT AUTHORS

Kristína Zgodavová ORCID: 0000-0001-7164-3810 (K.Z.) – executive director, Slovenská únia pre kvalitu inovácie a dizajn (Q-IMPULZ), Slovakia, e-mail: kristina.zgodavova@gmail.com.

Peter Bober ORCID: 0000-0002-8743-5220 (P.B.) – assistant professor, Technical University of Košice, Košice, Slovakia, e-mail: peter.bober@tuke.sk.

Aleš Bourek ORCID: 0000-0002-5481-3408 (A.B.) – assistant professor, Masaryk University, Brno, Czech Republic, e-mail: bourek@med.muni.cz.

Juliana Gabzdilová ORCID: 0000-0002-8125-1885 (J.G.) – assistant professor, Pavol Jozef Šafárik University in Košice, Košice, Slovakia, e-mail: juliana.gabzdilova@upjs.sk.

Jozef Babečka ORCID: 0000-0002-1592-0833 (J.B.) – associate professor, Catholic University in Ružomberok, Ružomberok, Slovakia, e-mail: jozef.babecka@ku.sk.

AUTHOR CONTRIBUTIONS

Conceptualisation, K.Z.; Methodology, K.Z., P.B.; Software, P.B.; Validation, A.B.; Formal analysis, A.B.; Investigation, K.Z., A.B.; Resources, J.G., A.B.; Data curation, J.B.; Original draft preparation, K.Z., P.B.; Review and editing, K.Z., P.B.; Visualisation, K.Z., P.B.; Supervision, A.B.; Funding acquisition, K.Z.

CONFLICTS OF INTEREST

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Dual-Horizon Quality Assurance for MBA and Doctoral Management Education: A Quality 5.0 Framework

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Róbert Czakó

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ABSTRACT

Purpose: This paper develops a quality-assurance architecture for comparing the added value of Master of Business Administration (MBA) and doctoral management education when application-oriented and research-oriented capabilities create organisational value through different mechanisms and time horizons.

Methodology/Approach: A targeted, mechanism-based conceptual synthesis integrates human-capital theory, educational-quality and assurance literature, workplace-transfer research, doctoral-education scholarship, and Quality 5.0. Sources are selected for direct construct relevance and integrated through a transparent six-layer mapping process.

Findings: The framework links programme purpose, capability formation, transfer context, near-term application, long-term capability, and organisational value. Its maturity levels and propositions show that apparent pathway superiority depends on outcome, context, and observation horizon.

Research Limitation/Implication: The framework requires empirical validation. A balanced initial target of 60 MBA and 60 doctoral management graduates is proposed for exploratory matched comparison; an a priori power analysis must confirm or increase the sample before fieldwork.

Originality/Value of paper: The model replaces credential ranking with human-centred, auditable, and time-sensitive quality assurance for programme design, employer dialogue, and continuous improvement.

Category: Conceptual paper

Keywords: quality 5.0; postgraduate management education; human capital; assurance of learning; workplace transfer

Research Areas: Quality 5.0; Strategic Quality Management

1 INTRODUCTION

Management education is increasingly expected to demonstrate value beyond enrolment, completion, and graduate satisfaction. Business schools, employers, and learners want evidence that advanced study improves managerial judgement, innovation, operational performance, and strategic adaptability. This question is difficult when programmes with different purposes are treated as substitutes (Orbánová & Urbančíková, 2026).

A Master of Business Administration (MBA) commonly emphasises the rapid integration and application of management knowledge. Doctoral management education commonly emphasises disciplined inquiry, methodological rigour, and the production or critical use of knowledge. Both pathways may strengthen human capital, but through different mechanisms and at different speeds.

Conventional assurance of learning (AoL) systems are essential but incomplete for this comparison. AoL demonstrates whether learners achieve programme-level competencies and whether assessment results inform curriculum improvement (Association to Advance Collegiate Schools of Business [AACSB International], 2020). It is usually strongest at the boundary that the educational institution controls: curriculum, assessment and graduation. Organisational value, however, emerges after that boundary. It depends on whether capability is transferred to work, whether the organisation provides opportunity and support, and whether an outcome is observed soon enough or long enough for the relevant mechanism to appear. Training-transfer research has long shown that learning does not automatically become workplace behaviour or performance (Baldwin & Ford, 1988; Blume, Ford, Baldwin, & Huang, 2010).

The time problem is especially important. Applied managerial tools may generate observable process improvements within a short period, while research capability may influence problem framing, evidence quality, innovation portfolios and strategic adaptation cumulatively. A single follow-up date can therefore favour what becomes visible first. Likewise, a single metric such as salary, promotion or self-reported competence cannot separate education from selection, experience, organisational opportunity and signalling effects. Quality assurance must acknowledge these attribution limits rather than hide them behind a composite score.

Quality 5.0 offers a human-centred design logic. Building on Industry 5.0, it treats advanced technology as a means of augmenting human capability, judgement, sustainability, and resilience rather than merely automating control (European Commission, 2021; Bucci, Fani, Rossi, Bandinelli, & Tucci, 2026).

Applied to management education, this logic calls for digitally enabled evidence with human interpretation. It also requires contextual meaning, ethical safeguards, and accountable curriculum decisions.

This paper is part of a wider research programme comparing the added value of MBA and doctoral management education in relation to human-capital efficiency.

Its specific research question is: How can postgraduate management programmes design a Quality 5.0 assurance architecture that captures both near-term application and long-term strategic capability without treating MBA and doctoral outcomes as interchangeable? The contribution is the Dual-Horizon Quality 5.0 Assurance Framework (DH-Q5AF), a conceptual model that connects programme purpose, capability formation, transfer conditions, temporal evidence and organisational value. Unlike a ranking or return-on-investment calculation, the framework asks whether each pathway creates the value it is designed to create, for whom, under what conditions and when.

2 METHODOLOGY

The study uses a targeted, mechanism-based conceptual synthesis. It is not a systematic literature review and does not report primary data. The method is appropriate because the problem spans several mature but partly separate literatures and requires explicit construct relationships, boundary conditions, and testable propositions. Six linked stages were followed.

First, the problem was bounded to postgraduate management education and two contrasting pathways: application-oriented MBA education and research-oriented doctoral management education. The aim was not to rank credentials, but to explain how their intended capability profiles may create different forms of organisational value.

Second, sources were selected purposively from five knowledge streams: human-capital theory; educational quality and assurance; learning and workplace transfer; professional and research doctorates; and Quality 5.0 with human-artificial intelligence (AI) complementarity. A source was retained when it directly defined a focal construct, explained a link in the education-to-value chain, specified a relevant boundary condition, or supplied an authoritative standard or policy frame. Priority was given to peer-reviewed research, established theoretical works, and authoritative institutional documents. The aim was conceptual coverage and complementarity, not exhaustive retrieval.

The retained sources were integrated in three steps. First, their core constructs and mechanisms were extracted. Second, each construct was mapped to one or more assurance layers and to its individual, programme, workplace, or organisational level. Third, convergent claims, tensions, and missing links were compared to define the framework's boundaries and propositions. This mapping links every framework component to a documented conceptual function while preserving differences among the source traditions.

Third, the synthesis specified six analytical layers: programme purpose, individual capability, transfer context, applied behaviour, organisational outcome, and time horizon. Keeping these layers separate prevents learning measures from being mislabelled as organisational performance and prevents organisational outcomes from being attributed to education without evidence of an intervening mechanism.

Fourth, the focal mechanism was mapped as programme design → capability formation → workplace enactment → organisational value. Transfer climate, job role, prior experience, sector, organisational size, digital maturity, and time since graduation were treated as moderators or controls. Selection, credential signalling, and career mobility were retained as rival explanations.

Fifth, the mapped relationships were converted into design propositions and a maturity model. The propositions are explanatory expectations rather than tested hypotheses. They specify what later empirical work should measure and the conditions under which the framework could be challenged.

Sixth, an empirical validation protocol was designed for the wider research programme. The initial target is 120 managers: 60 MBA graduates and 60 doctoral management graduates. Equal groups provide a balanced basis for 60 matched comparisons and feasible exploratory estimates of reliability, common-domain differences, and parsimonious adjusted associations. The target is not presented as sufficient for definitive causal inference. Before fieldwork, an a priori power analysis based on the final measures, the smallest meaningful effect, model complexity, and expected attrition must confirm or increase the recruitment target.

The 0–3-year near-term window is intended to capture early workplace application while programme exposure remains comparatively recent and transfer mechanisms can be documented. The 5+-year window captures cumulative strategic, research, leadership, and capability-building effects that often require repeated use and role progression (Baldwin & Ford, 1988; Blume et al., 2010; Creaton & Anderson, 2021). Years 3–5 form a transition interval for longitudinal observation; they are not excluded, and the two thresholds do not imply a causal discontinuity. Both windows are design choices to be tested empirically.

3 CONCEPTUAL FOUNDATIONS

3.1 Quality as Purpose, Transformation and Evidence

Educational quality has multiple legitimate meanings. Harvey and Green (1993) distinguish views that include excellence, consistency, fitness for purpose, value for money and transformation. For postgraduate management education, fitness for purpose and transformation are particularly relevant. Human-capital theory also frames education as an investment in productive capability rather than a credential alone (Becker, 1993). An MBA and a doctorate may therefore both be high quality while pursuing different transformations. Quality assurance requires a declared value profile before measurement begins; otherwise, the metric becomes the purpose by default.

AoL provides a disciplined foundation. Intended learning competencies, learning activities and assessment should be constructively aligned (Biggs, 1996), and assessment findings should close the loop through curriculum improvement (AACSB International, 2020). Nevertheless, programme-level learning evidence

cannot alone establish workplace value. A learner may demonstrate strategic analysis in a capstone assessment but lack the authority, data or support to use it at work. Conversely, organisational performance may improve for reasons unrelated to the programme. The assurance architecture must preserve this distinction.

3.2 Capability Profiles of MBA and Doctoral Pathways

The model uses knowledge, skills and attitudes (KSA) as a common vocabulary while allowing pathway-specific profiles. For MBA education, expected strengths often include cross-functional integration, decision speed, implementation, communication and operational improvement. For doctoral management education, expected strengths often include critical problem framing, methodological judgement, evidence evaluation, theory-informed explanation and sustained inquiry. These are stylised profiles, not fixed descriptions of every programme or graduate.

Professional-doctorate research challenges a simple academic/practical divide. Banerjee and Morley (2013) argue for practice-based doctoral education that integrates scholarly rigour with organisational problems. Creaton and Anderson (2021) show that doctoral impact is constructed through interactions among graduates, employers and professional networks and may develop over time. Neumann (2005) similarly notes differences and overlaps between professional doctorates and Doctor of Philosophy (PhD) programmes. Accordingly, DH-Q5AF does not equate MBA with practice and doctorate with theory. It treats pathway purpose as an empirical programme attribute that must be documented.

3.3 From Learning to Organisational Value

Transfer is the conversion mechanism. Baldwin and Ford (1988) identify trainee characteristics, training design and work environment as central influences on the generalisation and maintenance of learned material. Later meta-analytic evidence confirms that transfer depends on individual and contextual factors (Blume et al., 2010). The implication is decisive: the value of a postgraduate programme is jointly produced by the educational institution, the graduate and the organisation.

Organisational value is multidimensional. Near-term value may be visible in faster decisions, process redesign, cost avoidance, project delivery or the implementation of management tools. Long-term value may appear through innovation quality, strategic adaptability, evidence governance, capability building or resilience. Salary and promotion are useful contextual outcomes, but they are affected by labour markets, occupation and signalling. They should not be treated as direct proof of educational effectiveness.

3.4 Quality 5.0 and Human-AI Complementarity

Industry 5.0 reframes industrial transformation around sustainability, human-centricity and resilience (European Commission, 2021). Quality 5.0 extends this

orientation to quality systems. Its emerging literature argues that digital technologies must be aligned with human judgement, ethical governance and broader stakeholder value (Bucci et al., 2026). In management education, generative AI and analytics can support learning, evidence collection and decision modelling, but their presence also increases the value of verification, causal reasoning, methodological literacy and responsible judgement.

The automation–augmentation paradox explains why technology may replace some tasks while increasing the importance of complementary human capabilities (Raisch & Krakowski, 2021). Effective human–AI collaboration requires appropriate task allocation and a clear understanding of the limitations of both people and systems (Jarrahi, 2018).

The United Nations Educational, Scientific and Cultural Organization (UNESCO, 2023) likewise stresses human-centred, ethical, and pedagogically justified use of generative AI in education. A Quality 5.0 assurance system should therefore evaluate whether graduates can frame problems, validate outputs, document evidence, manage risk, and remain accountable – not merely whether they use AI.

4 THE DUAL-HORIZON QUALITY 5.0 ASSURANCE FRAMEWORK

As shown in Table 1, DH-Q5AF consists of six connected assurance layers. The layers make the value chain visible and auditable while preventing a single outcome from representing the whole system.

Table 1 – Assurance layers of the Dual-Horizon Quality 5.0 assurance framework

Layer	Core assurance question	Illustrative evidence	Principal risk
1. Programme purpose	What distinctive value is the programme intended to create?	Mission, intended capability profile, stakeholder needs	Credential categories substitute for an explicit purpose
2. Capability formation	What knowledge, skills and attitudes have learners demonstrably developed?	Direct assessment, authentic tasks, portfolios, rubrics	Self-report or course completion is treated as competence
3. Transfer context	Do graduates have opportunity, support, data and authority to apply capability?	Role analysis, supervisor assessment, transfer-climate indicators	The programme is blamed for blocked application, or credited for unrelated success
4. Near-term application (0–3 years)	What changes in behaviour and operational practice become visible relatively soon?	Implemented improvements, decision quality, project and process evidence	Only rapid, easily measured outcomes are valued
5. Long-term strategic capability (5+ years)	What cumulative effects appear in innovation, adaptation and evidence-based leadership?	Innovation portfolios, strategic decisions, capability building, resilience narratives	Late effects are inferred retrospectively without a credible chain of evidence
6. Organisational value and feedback	How are verified effects translated into curriculum and portfolio decisions?	Triangulated outcome dashboard, review minutes, curriculum actions	Measurement becomes reporting rather than continuous improvement

The model operates as a closed learning system. It begins with a programme-specific value profile, establishes baseline and context, assures capability formation, monitors enactment across two time horizons, triangulates organisational evidence and feeds findings back to programme design. Each cycle should record what changed, why it changed and what evidence would show improvement in the next cycle.

The dual horizon does not assign MBA effects to the short term and doctoral effects to the long term. It is an anti-bias device: both pathways are observed in both windows. Years 3–5 are treated as a transition interval, so the thresholds guide comparison without implying that an effect begins or ends at a fixed date.

4.1 Measurement Architecture

The framework recommends an evidence portfolio rather than a single ranking. It measures four domains: capability, transfer, application, and value. Capability evidence covers knowledge, skills, and attitudes through authentic assessment. Transfer evidence covers opportunity, supervisor support, data access, role fit, and implementation autonomy.

Application evidence documents changed behaviour and completed interventions. Value evidence uses financial and non-financial proxies aligned with the programme mission. The separation makes it easier to identify where the education-to-value chain is supported or interrupted.

Triangulation is essential. Graduate self-assessment reveals perceived development but is vulnerable to recall, identity and social-desirability effects. Supervisor assessment adds external observation but may reflect organisational politics or incomplete visibility. Organisational proxies provide relevance but rarely establish attribution on their own. A credible value claim requires convergence across at least two evidence types and a plausible mechanism connecting the programme to the outcome.

Digital tools can strengthen longitudinal tracking, portfolio analysis and dashboarding. In a Quality 5.0 system they must remain explainable and governed. Automated text analysis, for example, may help identify recurring capability themes in portfolios, but humans must define categories, verify ambiguous cases and decide whether the evidence warrants curriculum change. Data minimisation, consent, access control and documented decision responsibility are part of quality, not administrative additions.

4.2 Maturity Model

Institutions differ in their ability to implement longitudinal assurance. As shown in Table 2, the maturity model provides a development path rather than an accreditation label.

Table 2 – DH-Q5AF maturity model

Level	Dominant practice	Evidence profile	Improvement priority
0. Credential compliance	Inputs, attendance and completion dominate	Administrative records	Define programme purpose and graduate capability profile
1. Learning-outcome control	AoL operates at course and programme level	Rubrics, examinations, capstones	Connect assessed capability to authentic managerial practice
2. Transfer-aware assurance	Work context and opportunity to apply are monitored	AoL plus graduate and supervisor evidence	Separate education effects from transfer barriers and rival explanations
3. Dual-horizon assurance	Near-term and long-term outcomes are tracked for each pathway	Longitudinal, triangulated portfolio	Use matched comparisons and transparent attribution rules
4. Adaptive Quality 5.0 ecosystem	Human judgement and governed analytics continuously improve programmes	Integrated evidence with documented human oversight	Anticipate capability needs while protecting ethics, context and accountability

Progression requires stronger causal discipline, not merely more data. A Level 4 institution should be able to explain how a specific curriculum decision followed from evidence, who validated the evidence, how AI-assisted analysis was governed and how unintended effects were considered.

5 PROPOSITIONS AND DISCUSSION

Proposition 1: Purpose-aligned assurance will produce more valid comparisons of MBA and doctoral management education than undifferentiated credential ranking.

The same measure cannot fairly represent programmes whose intended transformations differ. Purpose alignment does not remove comparability; it makes comparison explicit. Common domains such as critical thinking, implementation and strategic judgement can be retained, but weights and evidence standards must reflect declared programme purposes. A programme should first be judged against its own value proposition and then compared on transparent shared dimensions.

Proposition 2: The apparent relative value of MBA and doctoral management education will vary with the observation horizon.

Outcomes have different maturation periods. An operational intervention may generate evidence within months, whereas the capacity to lead an innovation portfolio may emerge through repeated use. A cross-sectional study at one date confounds pathway with time. Dual-horizon measurement tests rather than assumes temporal differences and requires both pathways to be observed in both windows.

Proposition 3: Workplace transfer climate will moderate the relationship between demonstrated graduate capability and organisational value.

Capability is necessary but insufficient. A manager cannot apply advanced analytics without access to data, introduce process change without authority or sustain inquiry without organisational support. Measuring transfer climate protects the programme from invalid negative attribution and protects the organisation from invalid positive attribution. It also creates actionable dialogue: a low-value result may call for curriculum change, workplace redesign or both.

Proposition 4: Human-AI complementarity will strengthen organisational value when graduates possess verification, problem-framing and accountability capabilities.

AI can accelerate analysis and expand access to technical methods, but it can also create overconfidence, opaque reasoning and evidence-quality risks. The value of postgraduate education therefore shifts from tool exposure to responsible orchestration. MBA and doctoral pathways may contribute complementary strengths: rapid integration and implementation on one side; critical validation and methodological governance on the other. The proposition should be tested without assuming that either credential guarantees those strengths.

Proposition 5: Triangulated, context-adjusted evidence will reduce attribution error compared with self-report or organisational metrics used alone.

No observational design fully eliminates selection and endogeneity. Matching and statistical controls can improve comparability, while qualitative process evidence can test whether the proposed mechanism is credible. The framework therefore treats causal language as graded. Evidence may support association, contribution or plausible influence without necessarily supporting exclusive causation.

Together, the propositions shift the managerial question from “Which qualification wins?” to “Which capability profile fits the role, transfer environment and time horizon, and what evidence would justify that decision?” This is consistent with Quality 5.0 because it combines data discipline with human interpretation and stakeholder purpose.

6 IMPLICATIONS FOR PROGRAMME AND ORGANISATIONAL QUALITY

For business schools, DH-Q5AF requires programme differentiation that is empirically reviewable. Learning goals should state not only what graduates know at completion, but how capabilities are expected to transfer and what type of value should become visible over time. Alumni engagement then becomes part of assurance rather than marketing. Programme review boards should include employer and graduate evidence while retaining academic responsibility for interpretation.

For employers, the model provides a decision structure for educational investment. Sponsorship should be linked to the problem class and role trajectory. If the immediate need is cross-functional implementation, an application-oriented pathway may fit. If the need is research-led transformation, evidence governance or long-horizon innovation, doctoral capability may fit. The organisation must also provide a transfer environment; otherwise it purchases capability that it cannot use.

For learners, the framework clarifies expectations. A credential is not a uniform asset. Its realised value depends on prior experience, motivation, role, opportunity to apply learning and the time available for effects to develop. Transparent value profiles can reduce misleading comparisons based on title prestige alone.

For quality leaders, the maturity model provides an implementation roadmap. A practical first step is to map existing evidence to the six layers and identify breaks in the chain. Many institutions will discover strong learning evidence, weak transfer evidence and sporadic organisational outcomes. The next step is not necessarily a complex analytics platform. It may be a consistent supervisor instrument, an alumni portfolio protocol and a documented rule for how evidence changes curriculum.

7 FUTURE EMPIRICAL VALIDATION

The proposed validation uses a mixed-method matched-pair design. The planned starting target is 60 MBA and 60 doctoral management graduates with management experience, forming up to 60 pairs matched on relevant background and organisational characteristics. Equal group sizes support transparent matched and common-domain comparisons while remaining feasible for the first empirical test of a new framework.

This is an exploratory validation target, not a claim of population representativeness or definitive causal identification. Before recruitment, an *a priori* power analysis must use the final outcome measures, the smallest meaningful effect, the planned number of predictors, and expected attrition. If 60 participants per pathway are insufficient, recruitment must be increased. Propensity- or distance-based matching may supplement expert matching where data quality permits, and baseline differences must be reported.

Analysis should proceed in layers. Descriptive and reliability analyses first establish measurement quality. Paired or balanced group comparisons then estimate differences on common domains. Parsimonious regression models may test adjusted associations with pathway, experience, sector, role, and transfer climate, provided the achieved sample supports the planned model. Interaction effects should be estimated only where power is adequate.

Qualitative interviews with graduates and, where possible, supervisors should reconstruct critical incidents and test whether the proposed education-to-value mechanism is plausible. Multiple respondents and evidence types reduce common-

method bias. Pre-existing capability should be separated from educational development through baseline evidence or prospective follow-up where feasible. Findings must not be generalised beyond the sampled programmes, countries, and sectors without replication.

The purpose of validation is to test and revise the framework, not to confirm a predetermined hierarchy. Results should be reported by domain before any composite index is considered.

8 CONCLUSION

MBA and doctoral management education can create substantial but differently configured human-capital value. Comparing them through completion statistics, one-time satisfaction surveys or a single financial outcome obscures programme purpose, workplace transfer and time. The Dual-Horizon Quality 5.0 Assurance Framework addresses this problem by separating six assurance layers and requiring evidence across near-term and long-term horizons.

The framework makes four practical commitments. Quality is assessed against an explicit purpose; learning is separated from transfer and organisational outcome; digital evidence is governed by human judgement; and curriculum improvement is documented as part of the assurance cycle. Its maturity model allows institutions to progress from credential compliance to an adaptive Quality 5.0 ecosystem.

The paper provides a conceptual architecture rather than empirical proof. Its propositions and mixed-method validation protocol create a falsifiable research agenda. If supported and refined through empirical work, DH-Q5AF can help schools, employers, and learners decide which postgraduate management pathway fits a specific capability need, organisational context, and observation horizon.

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ABOUT THE AUTHOR

Róbert Czako ORCID: 0009-0004-6683-8495 – doctoral researcher, DTI University, Dubnica nad Váhom, Slovakia, e-mail: ing.robortczako@elektron.sk.

CONFLICTS OF INTEREST

The author declares that they have no conflict of interest. The funders had no role in the design of the study, in the collection, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

DISCLOSURE OF ARTIFICIAL INTELLIGENCE ASSISTANCE

OpenAI Codex was used to support language editing, structural refinement, response-to-reviewer organisation, and reference-format checking. The author defined the research problem, selected and verified the sources, evaluated every argument, and reviewed and approved the complete manuscript. No empirical data, statistical results, or citations were generated or fabricated using AI. The author accepts full responsibility for the content.



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Digital Technology Investment, Educational Technology, and Innovation Capacity in Egyptian Entrepreneurial Universities: An Integrated IPO Governance Framework with Quality Assurance

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Nihad ElHadidy, Nevien Khourshed, Iman Nassef, Kesmat AbdelAziz

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ABSTRACT

Purpose: This study investigates associations between Digital Technology Investment (DTI), Educational Technology (EdTech), Quality Assurance (QA), Innovation Capacity (IC), and Entrepreneurial University Characteristics (EUC) across twelve Egyptian universities within an integrated Input-Process-Output (IPO) governance framework.

Methodology/Approach: A cross-sectional survey used PLS-SEM (SmartPLS 4) with 5,000-subsample bias-corrected and accelerated (BCa) bootstrapping.

Findings: DTI was positively associated with IC ($\beta = 0.421$) and EUC ($\beta = 0.305$). EdTech partially mediated both associations (VAF = 41%; 38%), confirming pedagogical embedding as the value-generation mechanism. QA showed no moderation and a robust direct association with IC ($\beta = 0.269$, $p < 0.001$). IC predicted EUC ($\beta = 0.547$).

Research Limitation/Implication: The cross-sectional design precludes causal inference. Administrators should co-invest in EdTech alongside digital infrastructure and explore joint QA-digital governance structures.

Originality/Value of paper: This study offers the first integrated empirical test of a five-construct DTI-EdTech-IC-EUC governance chain with QA in a dual role, deriving a three-tier governance alignment model for emerging-economy higher education.

Category: Research paper

Keywords: digital technology investment; educational technology; entrepreneurial university; innovation capacity; quality assurance

Research Areas: Management of Technology and Innovation

1 INTRODUCTION

The paradox is that, apart from the education results, universities invest high amounts of resources and efforts in developing digital technologies, but do not get the expected amount of innovation performance and entrepreneurial outcomes (Alamri, Alshammari, & Al-Shehri, 2023). This pattern is evident across Egyptian higher education institutions. Within the last decade, the utilization of digitization in higher educational institutions (whether public or private), with the aid of national digital transformation visions, such as Egypt Vision 2030 (Ministry of Higher Education and Scientific Research [MoHESR], 2024), has been widely adopted through digital tools and platforms such as: Learning Management System (LMS), Cloud Computing, and Data Analytics tools. The performance of Egyptian universities on global innovation and entrepreneurial indicators (Times Higher Education, 2024), however, is low, suggesting that digital investments so far have not yet translated into the expected innovation outcomes at universities.

This gap is fundamentally a governance challenge rather than a procurement problem. Institutional performance depends not only on resource acquisition but on the governance structures through which resources are deployed (Kezar, 2018). Two governance mechanisms are especially consequential: Educational Technology (EdTech) the organisational capability through which digital investments are converted into pedagogical and administrative practice and Quality Assurance (QA) the governance system setting accountability standards and driving continuous improvement. A specific condition characterising many Egyptian universities is administrative silo structures, in which digital transformation units, QA offices, and EdTech centres operate as functionally disconnected departments without cross-functional coordination (Shamsi, 2024; Hussein & El-Naggar, 2025).

Three gaps motivate this study. First, the process through which digital investment is associated with innovation capacity has not been tested as a mediated pathway in governance-fragmented higher education systems. Second, QA's widely assumed moderating role in institutional change (Harvey & Green, 1993; Munoz & Harb, 2024) has not been tested where QA and digital governance operate as silos. Third, the association between digital transformation inputs, innovation capacity, and entrepreneurial outputs has not been empirically modelled within a single integrated framework for the Egyptian context.

This study makes four contributions: (1) an integrated Input-Process-Output (IPO) governance model combining Dynamic Capabilities Theory, Resource-Based View, and IPO logic; (2) the first empirical test of QA's dual governance role simultaneously as hypothesised moderator and direct predictor in this context; (3) empirical validation of the DTI-EdTech-IC-EUC perceptual association chain; and (4) a three-tier governance alignment model (Foundation, Conversion, Governance Integration) providing actionable sequencing guidance (Marquez & Luna, 2022). Table 1 positions the present study against the five closest empirical comparators.

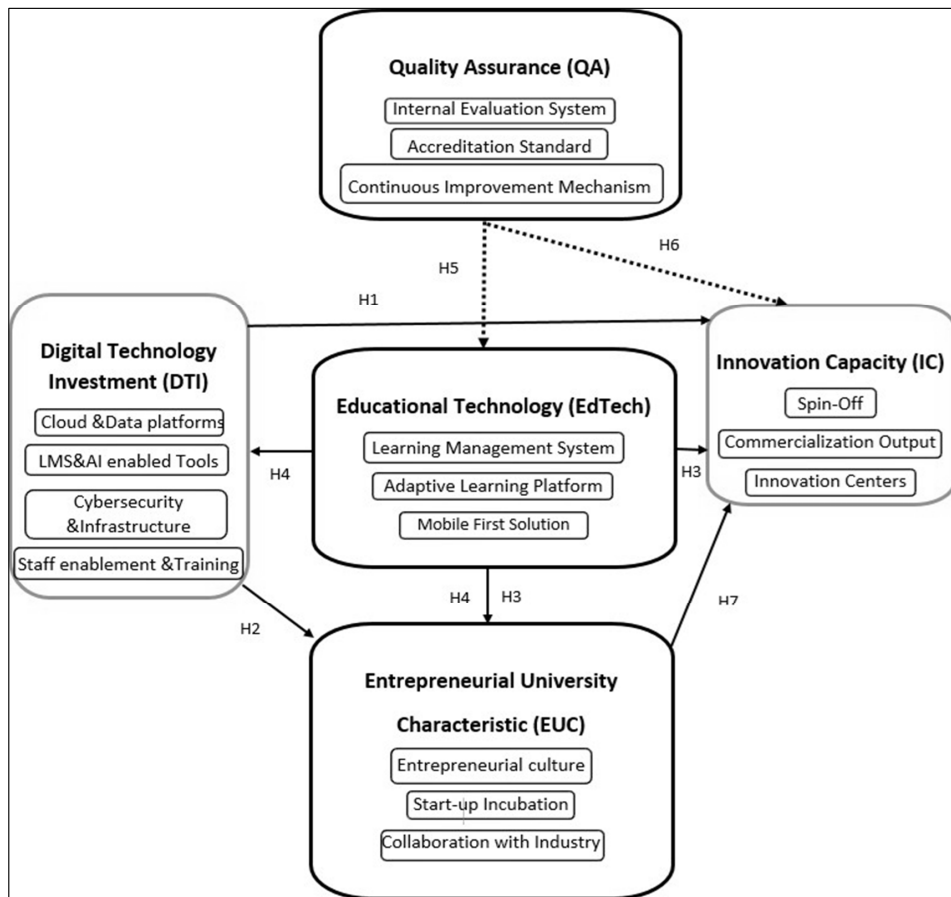


Figure 1 – IPO governance model: Conceptual framework

Figure 1 presents the conceptual framework illustrating the proposed IPO governance model with all hypothesised relationships.

Table 1 – Systematic comparison with closest empirical comparators

Study	Constructs	Key Paths	Method & Context	Theory	Gap vs. Present Study
Alamri et al. (2023) Computers & Education	Digital investment readiness; EdTech; Institutional performance	Digital investment → EdTech → Performance	Survey; CB-SEM; Saudi Arabia; N = 312	TAM; Institutional theory	No IC or EUC; no QA; individual constructs only
Ghosh, Rahman, and Karim (2024) Information & Management	DTI; Resilience; Performance	DTI → Resilience → Performance	Panel data; 6 countries; N = 218	RBV; Dynamic Capabilities	No EdTech mediator; no QA; no EUC

Study	Constructs	Key Paths	Method & Context	Theory	Gap vs. Present Study
Kim, Lim, and Park (2024) Computers & Education	Digital learning ecosystem; Faculty engagement; Innovation	Ecosystem → Engagement → Innovation	PLS-SEM; South Korea; N = 247	Dynamic Capabilities	No QA; no EUC; no IPO framework
Munoz and Harb (2024) Assessment & Evaluation	QA; Digital learning; Innovation	QA → Digital → Innovation	Mixed methods; Lebanon; N = 189	Continuous improvement	No DTI; QA as input not moderator
Guerrero, Heaton, and Urbano (2021) Technovation	Digital capabilities; Intrapreneurial capacity; EUC	Digital → IC → EUC	PLS-SEM; Spain/Mexico; N = 423	Entrepreneurial university	No DTI; no QA; no EdTech
Present Study (ElHadidy, Khourshed, Nassef, & AbdelAziz, 2026)	DTI; EdTech; QA; IC; EUC	DTI → IC → EUC; EdTech mediates (VAF = 41%/38%); QA direct ($\beta = 0.269$)	PLS-SEM; Egypt; N = 360; 12 universities	RBV+Dynamic Cap.+IPO	First with all 5 constructs+QA dual role

Note: CB-SEM = covariance-based SEM; RBV = Resource-Based View; TAM = Technology Acceptance Model; VAF = Variance Accounted For.

2 LITERATURE REVIEW

2.1 Digital Technology Investment and Institutional Performance

DTI includes investment in AI-systems, Cloud-framework, Cyber-security and in Digital Skills as institutional investments. If Digital Infrastructure is understood as a strategic resource in the institutional deployment, based on Resource Based View (Barney, 1991), usage of this resource can be exploited and turn into a value if well managed. Cohen and Levinthal (1990) Absorptive capacity explain how DTI can have an influence, where as higher DTI increases the institutional Absorptive capacity, and eventually the better recognition, assimilation and application of DTI helps an institution's better capacity to produce knowledge and innovation. Prior research confirms that governance quality and deployment capacity both condition how digital investment translates into institutional performance.

2.2 Educational Technology as Organisational Capability

The concept of EdTech as the organisational sensing-and-integrating capability (Teece, 2007, 2023) positions it as the primary mechanism through which digital investments are converted into pedagogical and administrative practice. The opportunity identified through digital investment and the dimension grasped is the adoption and embedding of EdTech tools into institutional routines through faculty

practice. Kim et al. (2024) and Aboagye, Anane, and Boateng (2025) confirm significant mediation effects, with mediating associations between EdTech integration and innovation performance partially validated DTI also contributes directly through non-EdTech administrative channels.

2.3 A Governance Structure with a Focus on Quality Assurance (QA)

Modern QA systems include a focus on incremental improvements, are performance based and track strategic performance measures (Harvey & Green, 1993; Stensaker, 2018). The theory literature offers two conflicting suggestions: One is that there is a set of digital transformation paths between the adopted and moderated set of digital transformation paths, and the second is that the institutional quality dimensions between the digital and quality intentions are moderated by a QA mindset towards adoption somewhere between the two sets of paths identified above. However, as per the governance fragmentation theory, implementation review mechanisms in nature of autonomous QA mechanisms helps to enable QA to influence the strength of digital pathways but on the other hand, QA cannot influence strength of digital pathways in case of administrative silos. Where governance integration is absent, QA's moderating potential remains latent a theoretical prediction tested empirically in the present study.

2.4 Innovation Capacity and Entrepreneurial University Performance

There is substantial evidence that Innovation Capacity is a strong predictor of entrepreneurial university outcomes, encompassing faculty entrepreneurial competencies, cross-disciplinary collaboration networks upon which third-mission outcomes depend, and research commercialisation pipelines. Entrepreneurial University theory (Etzkowitz, 2017; Klosthen et al., 2019) positions IC as the necessary precondition for EUC: start-up creation, technology commercialisation, and industry partnerships cannot emerge without prior IC development. The sequential model DTI → EdTech → IC → EUC represents a governance chain in which each stage is a necessary but not sufficient condition for the subsequent stage. Table 2 summarises the theoretical basis for each hypothesised path, the proposed mechanism, and the alternative model that would be rejected if the hypothesis is supported.

Table 2 – Theory-Path linkage and alternative models rejected

Path	Theory	Mechanism	Alternative Model Rejected
DTI → IC (H1); DTI → EUC (H2)	RBV (Barney, 1991); Absorptive Capacity (Cohen & Levinthal, 1990)	DTI creates absorptive capacity enabling knowledge creation and innovation	Null: DTI has no association with IC — rejected ($\beta=0.421$, $p<0.001$)
DTI → EdTech → IC/EUC (H3, H4)	Dynamic Capabilities (Teece, 2007, 2023)	EdTech is the sensing-seizing-transforming capability converting DTI to operational competence	Full mediation: DTI has no direct association — rejected; Zero mediation — rejected

Path	Theory	Mechanism	Alternative Model Rejected
QA moderation (H5, H6) — not supported	Governance Fragmentation (Harvey & Williams, 2010; Shamsi, 2024)	In silo-structured systems, QA cannot penetrate digital transformation pathways	Strong moderation rejected (both CIs span zero; $f^2 < 0.005$)
QA → IC direct	Quality Culture Theory (Harvey & Green, 1993; Stensaker, 2018)	QA contributes through autonomous quality culture mechanisms	Null: QA has no association with IC — rejected ($\beta = 0.269$, $p < 0.001$)
IC → EUC (H7)	Entrepreneurial University Theory (Etzkowitz, 2017; Klofsten et al., 2019)	IC provides knowledge pipelines and faculty competence upon which EUC depends	Direct DTI-to-EUC without IC: partially rejected ($\beta = 0.547$)

2.5 Research Hypotheses

The following hypotheses operationalise the five possible associations, mentioned above, between DTI, EdTech, QA, and IC, and EUC based on the theoretical framework:

H1: DTI is positively associated with IC.

H2: DTI is positively associated with EUC.

H3: EdTech partially mediates the association between DTI and IC.

H4: EdTech partially mediates the association between DTI and EUC.

H5: QA positively moderates the association between DTI and EdTech.

H6: QA positively moderates the association between EdTech and IC.

H7: IC is positively associated with EUC.

3 METHODOLOGY

3.1 Research Design

This is a quantitative, deductive, cross-sectional study. All reported associations are perceptual measured from staff assessments of institutional conditions and the design does not permit causal inference. Reverse causality cannot be excluded. Egypt was selected because digital investment is substantial, governance fragmentation is structurally documented (Shamsi, 2024), and the conditions for testing the governance fragmentation hypothesis are present. PLS-SEM was selected for its robustness with ordinal Likert-scale data, predictive orientation alignment, and suitability for moderately sized samples with complex latent variable structures (Hair, Hult, Ringle, & Sarstedt, 2022).

3.2 Sample and Data Collection

The target population included academic staff, administrative staff, digital transformation staff, e-learning staff, and Quality Management staff from Egyptian universities. For this study, 12 Egyptian universities were selected based on two factors: (1) explicit entrepreneurial orientation, which was documented in institutional mission statements and strategic plans; (2) active digital transformation programmes documented in institutional records and IT departments' documentation. Public, as well as private institutions were present, reflecting metropolitan and regional locations. All respondents participated in the study and proportional representation was ensured by purposeful stratified sampling by the type of institution the respondent was in, as well as plays a role in. To account for the issue of unit of analysis, Intraclass correlation coefficients were computed: ICC(1) ranged from 0.12 to 0.19 and ICC(2) from 0.54 to 0.68 for each of the five constructs: ICC(1) = 0.12 – 0.19 and ICC(2) = 0.54 – 0.68, which is considered moderate agreement within institutions. With regard to these values, and because of the multi-role of the surveyed sample (faculty, administrators, IT staff and QA officers), constructs are perceived measures at the individual level and not indicator values at the institutional level; clustering is therefore taken into account by employing robust standard error values.

Participants were invited through formal contacts in the institutions, via institutional email lists and information visits were made; informed consent was obtained before participation and anonymity was guaranteed. A total of 360 (72%) valid responses were obtained after a variety of multivariate outliers on Mahalanobis D^2 screening ($p < 0.001$) and incomplete response items were eliminated, which met or exceeded the minimum number (138) based on the G*Power 3.1 calculation of statistical power with $f^2 = 0.15$, $\alpha = 0.05$, power = 0.80, predictors = 5 (number of predictors). The smallest hypothesised interaction effect ($f^2 = 0.02$) was built up with a power of 0.89, which was an adequate sensitivity. Sample demographic profile are given in Table 3.

3.3 Measure

DTI, EdTech, QA, IC and EUC were measured using four reflective constructs for each. Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) derived from validated instruments were used to measure staff assessments of institutional conditions. Items were translated from English to Arabic through a translation-back-translation procedure; discrepancies were resolved through bilingual expert panel consensus. Expert content review involved seven subject-matter experts in educational technology, information systems management, and quality assurance (CVR > 0.80 for all items). A pilot study ($n = 50$) confirmed Cronbach's $\alpha > 0.80$ for all constructs. Common method bias was mitigated through random item ordering, psychological separation of predictor and outcome constructs across questionnaire sections, and anonymity assurance; post-hoc

Harman's single-factor test confirmed no single factor accounted for more than 50% of variance. All 20 items and their sources are provided in Appendix A.

3.4 Data Analysis

Initial screening in SPSS 26 confirmed distributional adequacy (skewness $\leq \pm 2$; kurtosis $\leq \pm 7$ for all indicators) and the absence of missing data and multivariate outliers. PLS-SEM was implemented in SmartPLS 4.0.9.2 (Ringle, Wende, & Becker, 2025) using the path weighting scheme, consistent PLS (PLSc) estimates for reflective constructs (Dijkstra & Henseler, 2015), and 5,000-subsample nonparametric bootstrap resampling with no sign changes and bias-corrected and accelerated (BCa) 95% confidence intervals for all path coefficients and indirect effects. Moderation was tested using the two-stage product-indicator approach (Sarstedt, Ringle, & Hair, 2019). Post-hoc Gaussian Copula endogeneity tests (Park & Gupta, 2012) were non-significant (all $p > 0.10$). FIMIX-PLS segmentation detected no significant latent subgroups. PLSpredict (10-fold cross-validation) confirmed positive Q^2 values for all endogenous indicators.

Table 3 – Demographic characteristics of respondents (N = 360)

Variable	Category	n	% (valid)
University affiliation (k = 12 institutions) ^a	October University for Modern Sciences & Arts (MSA)	95	26.4
	Ain Shams University	40	11.1
	Alexandria University	31	8.6
	Nile University	28	7.8
	Zewail City of Science and Technology	28	7.8
	British University in Egypt (BUE)	27	7.5
	Egypt-Japan University of Science and Technology (E-JUST)	23	6.4
	The American University in Cairo (AUC)	21	5.8
	Future University in Egypt (FUE)	20	5.6
	German University in Cairo (GUC)	17	4.7
	Misr International University (MIU)	11	3.1
	Cairo University	11	3.1
	Galala University	8	2.2
	Total	360	100.0
Respondent role	Innovation centre staff	83	23.1
	IT/Digital transformation manager	78	21.7
	EdTech/LMS specialist	67	18.6
	Vice dean/Strategic planning admin	46	12.8
	Faculty (innovation/e-learning)	34	9.4

Variable	Category	n	% (valid)
	Other	30	8.3
	QA officer	22	6.1
	Total	360	100.0
Academic rank	Assistant Professor	108	30.0
	Associate Professor	81	22.5
	Assistant Lecturer/Lecturer	81	22.5
	Professor	57	15.8
	Not applicable (professional services)	33	9.2
	Total	360	100.0
Gender	Man	192	53.3
	Woman	163	45.3
	Non-binary	3	0.8
	Prefer not to say	2	0.6
	Total	360	100.0
Primary appointment	Teaching-only	113	31.4
	Teaching and Research	113	31.4
	Research-only	73	20.3
	Professional services/admin	61	16.9
	Total	360	100.0
Age group (valid N = 359) ^b	25–34	152	42.3
	35–44	81	22.6
	Under 25	61	17.0
	45–54	46	12.8
	55–64	15	4.2
	65 or above	4	1.1
	Prefer not to say	1	0.3
	Total	360	100.0
Primary duties	QA duties	124	34.4
	Both QA and Innovation	108	30.0
	Innovation hub projects	96	26.7
	Neither	32	8.9
	Total	360	100.0

Note: ^a Original submission listed MSA under two row labels; merged entry: October University for Modern Sciences & Arts (MSA), n = 95; data collected from 12 distinct institutions. ^b Age group: 1 respondent preferred not to disclose (valid N = 359). ^c Contract type: 4 respondents did not complete this item (valid N = 356). All structural-model analyses conducted on full N = 360.

4 RESULTS

4.1 Measurement Model

All 20 indicator loadings were satisfactory (range: 0.736 – 0.912), exceeding the 0.70 threshold. Cronbach's alpha (0.841 – 0.902) and composite reliability (0.879 – 0.931) exceeded 0.70. AVE ranged from 0.63 (QA) to 0.73 (IC), confirming convergent validity. All HTMT ratios were below 0.85, confirming discriminant validity. All VIF values were below 3.3, ruling out collinearity. Table 4 and Table 5 present the full measurement model results.

4.2 Structural Model and Hypothesis Testing

The model demonstrated substantial explanatory power: $R^2(IC) = 0.691$; $R^2(EUC) = 0.723$. Model fit was acceptable: SRMR = 0.041 (below 0.08); $Q^2(IC) = 0.481$; $Q^2(EUC) = 0.537$. Table 6 presents all structural path results with BCa confidence intervals, and Figure 2 presents the path diagram. Effect sizes and collinearity diagnostics are presented in Table 7.

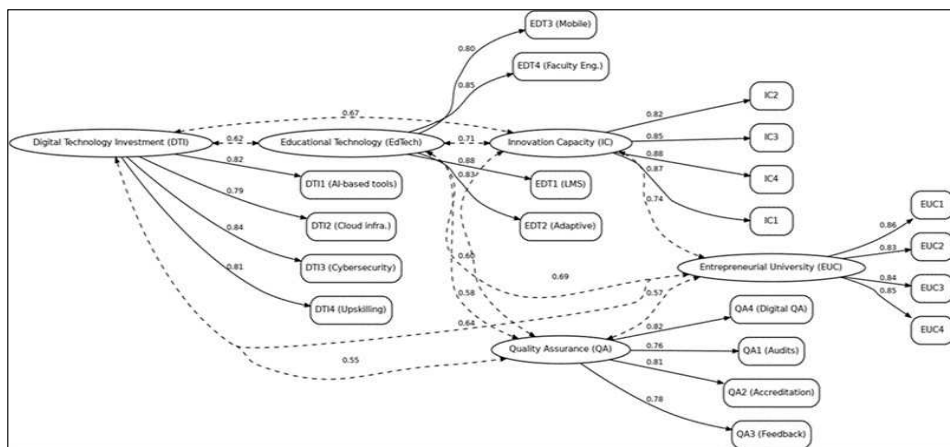


Figure 2 – Structural model with standardised path coefficients (SmartPLS 4)

4.3 Mediation Analysis

Bootstrapped indirect effects confirmed partial mediation for both EdTech pathways. DTI → EdTech → IC: $\beta_{\text{indirect}} = 0.201$ ($t = 4.527$, $p < 0.001$, 95% BCa CI [0.113, 0.291]), VAF = 41%. DTI → EdTech → EUC: $\beta_{\text{indirect}} = 0.183$ ($t = 3.902$, $p < 0.001$, 95% BCa CI [0.094, 0.274]), VAF = 38%. VAF was calculated as: $VAF = \text{indirect effect} / (\text{indirect} + \text{direct effect}) \times 100$. Both mediations are partial: VAF values of 41% and 38% indicate that EdTech accounts for substantial but non-exclusive shares of the DTI-IC and DTI-EUC associations. The remaining direct DTI associations (H1, H2) confirm that digital investment is also associated with innovation outcomes through non-EdTech channels, including administrative digitisation and research infrastructure.

4.4 Moderation Analysis

Both interaction terms were statistically non-significant and associated with negligible effect sizes: DTI $\times$ QA $\rightarrow$ EdTech ($\beta = 0.062$, $t = 1.214$, $p = 0.225$, $f^2 = 0.004$, 95% BCa CI $[-0.038, 0.163]$) and EdTech $\times$ QA $\rightarrow$ IC ($\beta = 0.047$, $t = 0.983$, $p = 0.327$, $f^2 = 0.003$, 95% BCa CI $[-0.048, 0.142]$). The confidence intervals for both interaction terms span zero and are centered near zero, providing convergent evidence against meaningful moderation in the current sample. Simple slopes analysis at ± 1 SD of QA confirmed parallel slopes across all predictor values. The power sensitivity analysis (G*Power 3.1) confirmed 0.89 power to detect $f^2 = 0.02$ at $\alpha = 0.05$, ruling out a Type II error explanation for the null moderation findings. The direct QA $\rightarrow$ IC association ($\beta = 0.269$) remained robust when interaction terms were included, confirming QA's positive association with innovation capacity operates independently of any interaction effects.

Table 4 — Reliability and convergent validity statistics (SmartPLS 4)

Construct	Loading range	AVE	CR	Cronbach's α	HTMT max
DTI	0.798 – 0.878	0.66	0.89	0.85	0.825
EdTech	0.741 – 0.912	0.71	0.91	0.88	0.827
QA	0.736 – 0.856	0.63	0.87	0.83	0.408
IC	0.768 – 0.901	0.73	0.92	0.89	0.823
EUC	0.753 – 0.889	0.71	0.91	0.88	0.827

Note: AVE = Average Variance Extracted; CR = Composite Reliability; HTMT max = highest inter-construct HTMT ratio. All HTMT ratios below 0.85 confirm discriminant validity (Henseler, Ringle, & Sarstedt, 2015).

Table 4 shows that all constructs meet the established for reliability and convergent validity threshold. The Haverotrait – MontoTrait (HTMT) ratio matrix, as presented in Table 5 shows that all the pairs of constructs exhibited (cross sectional) discriminant validity.

Table 5 — Heterotrait–monotrait (HTMT) ratio matrix (SmartPLS 4)

Construct	DTI	EdTech	QA	IC	EUC
DTI	—				
EdTech	0.825	—			
QA	0.232	0.408	—		
IC	0.795	0.823	0.373	—	
EUC	0.818	0.827	0.380	0.822	—

Note: All off-diagonal values < 0.85 confirm discriminant validity (Henseler et al., 2015).

Table 6 presents the structural model results with standardised path coefficients, bootstrap statistics, and BCa confidence intervals for all direct, indirect, and interaction effects.

Table 6 — Complete structural model results with bootstrap confidence intervals

H	Path	β	t-value	p	95% CI (BCa)	Decision
Direct Associations						
H1	DTI → IC	0.421	6.238	< 0.001	[0.289, 0.554]	Supported
H2	DTI → EUC	0.305	4.913	< 0.001	[0.175, 0.435]	Supported
H7	IC → EUC	0.547	8.104	< 0.001	[0.412, 0.681]	Supported
—	QA → IC (direct)	0.269	3.881	< 0.001	[0.132, 0.406]	Supported
—	DTI → EdTech	0.681	10.442	< 0.001	[0.558, 0.804]	—
—	EdTech → IC	0.478	7.021	< 0.001	[0.344, 0.612]	—
—	EdTech → EUC	0.382	5.442	< 0.001	[0.245, 0.519]	—
Indirect Associations via EdTech						
H3	DTI → EdTech → IC	0.201	4.527	< 0.001	[0.113, 0.291]	Supported (VAF=41%)
H4	DTI → EdTech → EUC	0.183	3.902	< 0.001	[0.094, 0.274]	Supported (VAF=38%)
	Interaction Terms (Moderation)					
H5	DTI × QA → EdTech	0.062	1.214	0.225	[-0.038, 0.163]	Not supported
H6	EdTech × QA → IC	0.047	0.983	0.327	[-0.048, 0.142]	Not supported

Note: 5,000-subsample nonparametric bootstrap; BCa confidence intervals. $R^2(\text{IC}) = 0.691$; $R^2(\text{EUC}) = 0.723$; $\text{SRMR} = 0.041$; $Q^2(\text{IC}) = 0.481$; $Q^2(\text{EUC}) = 0.537$. VAF = indirect/(indirect+direct)×100. Non-significant interaction CIs spanning zero rule out meaningful moderation.

Table 7 demonstrates these results with effect size (f^2) estimates and collinearity diagnostics (VIF), confirming the practical significance and statistical robustness of each path.

Table 7 — Effect sizes (f^2) and collinearity diagnostics (VIF)

Predictor → Outcome	f^2	Interpretation	VIF (inner)	VIF (outer max)
DTI → IC	0.198	Medium	1.87	2.14
DTI → EUC	0.121	Small-medium	1.92	2.14
DTI → EdTech	0.344	Large	—	—
EdTech → IC	0.312	Large	2.03	2.31
QA → IC (direct)	0.121	Small-medium	1.64	1.89
IC → EUC	0.287	Medium-large	2.11	—
DTI × QA → EdTech (interaction)	0.004	Negligible	—	—
EdTech × QA → IC (interaction)	0.003	Negligible	—	—

Note: f^2 thresholds: small = 0.02, medium = 0.15, large = 0.35 (Hair et al., 2022). All VIF values < 3.3 rule out collinearity. Sensitivity analysis: 0.89 power to detect $f^2=0.02$, ruling out Type II error for null moderation.

5 DISCUSSION

5.1 DTI and the Investment-Innovation Gap

The positive direct associations between DTI and IC ($\beta = 0.421$) and EUC ($\beta = 0.305$) are consistent with the RBV prediction that higher digital resource endowments are associated with greater institutional innovation capacity, controlling for EdTech and QA. More importantly, VAF values reveal that over one-third of DTI's total association with IC is channelled through the EdTech pathway. Institutions with higher DTI scores but lower EdTech capability capture approximately 60% of the innovation association their investment level would theoretically predict the perceptual expression of the investment-innovation gap (Alamri et al., 2023). These associations are not causal; longitudinal designs are needed to establish whether higher DTI temporally precedes improvements in IC, or whether institutions with higher pre-existing IC invest more strategically in digital infrastructure.

5.2 Governance Capability as Rate-Limiting EdTech

Amongst all the predictors, at the institutional level, EdTech has the highest f^2 ($f^2 = 0.312$ vs. DTI direct $f^2 = 0.198$), meaning that at the institutional level, digital investment is most related to innovation capacity through EdTech. This is in line with Dynamic Capabilities Theory (Teece, 2007) which involves the capability of the enterprise to sensing, seizing and transforming to transform the potential of the technological infrastructure in the pedagogic and administrative activity. The partial mediation with VAF of 41% and 38% seem logical: In the first case, the variance in EdTech is the pedagogical channel to the possible contribution of DTI, in the second instance, there is no pedagogic channel (i.e., EdTech) and the variance amounts to the direct DTI relationships of coverage of the administrative and the research infrastructure and data analytics pathways. These findings extend Kim et al. (2024) by confirming the EdTech mediation pathway in an Egyptian governance-fragmented context and by adding EUC as a distal outcome.

5.3 QA: Direct Association, Not Conditional Amplifier

The most theoretically significant finding is the combination of null moderation and robust direct QA association. The governance fragmentation hypothesis (Harvey & Williams, 2010; Shamsi, 2024) predicts precisely this pattern: where QA and digital governance operate as administrative silos, QA cannot penetrate digital transformation pathways but contributes to institutional innovation through autonomous quality culture mechanisms. The negligible interaction f^2 values (0.004, 0.003) and zero-spanning CIs are not consistent with a meaningful moderating association being present and undetected. However, the direct QA $\rightarrow$ IC association ($\beta = 0.269$) confirms that staff who perceive stronger QA systems at their institution also report higher institutional innovation capacity consistent with quality culture mechanisms (Harvey & Green, 1993; Stensaker,

2018) operating independently of digital transformation integration. This repositions QA's governance role as institutionally contingent: a conditional amplifier in governance-integrated systems, an autonomous quality culture driver in governance-fragmented ones.

5.4 Three-Tier Governance Alignment Model

The pattern of findings supports a three-tier governance alignment model. Tier 1 (Foundation) addresses digital infrastructure investment conditionally associated with innovation outcomes, but capturing only 60% of potential without Tier 2. Tier 2 (Conversion) addresses EdTech capability development the rate-limiting governance competence that converts DTI from latent resource to operational innovation capacity. Tier 3 (Governance Integration) addresses structural alignment between QA and digital transformation governance the mechanism that would activate QA's latent moderating potential. Institutions whose staff report high DTI but low EdTech adoption, and whose QA and digital units operate as silos, are predicted by the model to underperform relative to their investment level precisely the pattern observed in the Egyptian higher education system.

5.5 Practical and Policy Implications

For university administrators, four implications follow from these perceptual associations. First, EdTech capability investment should be treated as a mandatory co-investment alongside digital infrastructure rather than as an implementation detail. Second, EdTech adoption should be institutionalised through formal policy, promotion review incentives, and monitored utilisation metrics. Third, joint QA-ICT steering committees are the practical mechanism for beginning governance integration and potentially activating QA's moderating potential in future periods. Fourth, IC should be the primary measurable performance target for digital transformation strategies, with EUC indicators as distal benchmarks. At the national policy level, NAQAAE should incorporate EdTech adoption metrics and QA-digital governance integration evidence into its accreditation standards, creating institutional incentives for Tier 2 and Tier 3 development.

6 LIMITATIONS

Several limitations are central to the interpretation of findings and should inform future research design. First, the cross-sectional single-source perceptual design is the primary limitation: all five constructs are measured from the same respondents at the same time point, preventing causal inference and creating potential for common method variance despite procedural controls (Harman test confirmed no single factor > 50% of variance). Second, they are perceptual constructs and not necessarily based on administrative and/or financial data because they are based on staff's perception of what is going on in the institution. Third, the 12 universities purposeful sample highly entrepreneurial and digital transformed, is not

generalizable to the entire population of the universities in Egypt. Fourth: ICCs were not above the conventional level of aggregation (ICC(2) range 0.54 – 0.68 vs. recommend ≥ 0.70) so constructs should not be regarded as measures of aggregation conditions, but the individual. Fifth, data were clustered at the institution level ($N = 12$ clusters) which decreased the power of multilevel analyses, between institutions robust standard errors were used, but larger cluster samples with multilevel SEM will better estimate between institutions effects.

7 CONCLUSION

This study examined perceptual associations between digital technology investment, educational technology, quality assurance, innovation capacity, and entrepreneurial university characteristics across 12 Egyptian universities. Five of seven hypotheses were supported. EdTech mediates 41% and 38% of DTI's associations with IC and EUC respectively, confirming pedagogical embedding as the critical conversion mechanism. QA shows no detected moderation of digital transformation pathways but maintains a robust direct association with IC ($\beta = 0.269$), consistent with autonomous quality culture mechanisms operating in governance-fragmented institutional environments. IC is the primary proximate predictor of EUC ($\beta = 0.547$), validating the IPO output logic.

The three-tier governance alignment model Foundation (DTI), Conversion (EdTech), and Governance Integration (QA-digital alignment) provides a diagnostic and sequencing framework applicable to any emerging-economy higher education system where digital investment is substantial but governance integration is incomplete. Digital transformation is not a procurement challenge but a governance sequencing challenge. Future research should pursue longitudinal panel designs to establish temporal precedence, incorporate objective institutional performance data for construct triangulation, and extend the model to multi-country comparative studies to assess the boundary conditions of the governance fragmentation hypothesis.

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ABOUT AUTHORS

Nihad ElHadidy ORCID: 0009-0002-7752-0891 (N.E.) – PhD Candidate, Department of Business Information Systems, Arab Academy for Science, Technology and Maritime Transport (AASTMT), Alexandria, Egypt, e-mail: nihad@aast.edu.

Nevien Khourshed ORCID: 0000-0002-7491-5778 (N.K.) – Professor of Operations Management, Marketing and International Business, Arab Academy for Science, Technology and Maritime Transport (AASTMT), Alexandria, Egypt, e-mail: nevienkhourshed@aast.edu.

Iman Nassef ORCID: 0009-0005-3401-6371 (I.N.) – Assistant Professor, College of Computing and Information Technology, Arab Academy for Science, Technology and Maritime Transport (AASTMT), Alexandria, Egypt, e-mail: iman.nassef@aast.edu.

Kesmat AbdelAziz ORCID: 0000-0003-3164-934x (K.A.) – Assistant Professor, Department of Business Information Systems, Arab Academy for Science, Technology and Maritime Transport (AASTMT), Alexandria, Egypt, e-mail: kesmat.yehia@aast.edu.

AUTHOR CONTRIBUTIONS

Conceptualisation, N.E., N.K. and I.N.; Methodology, N.E., N.K., I.N. and K.A.; Software, N.E.; Formal analysis, N.E.; Investigation N.E.; Resources, N.E.; Data curation, N.E.; Original draft preparation, N.E.; Review and editing, N.K., K.A. and I.N.; Visualisation, N.E.; Supervision, N.K., I.N. and K.A.; Project administration, N.K., I.N. and K.A.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest. The funders had no role in the design of the study, in the collection, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

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The authors declare that no artificial intelligence tools were used in conducting the research, data collection, analysis, or interpretation of findings. All research content was developed, written, and validated exclusively by the authors. The dataset supporting the conclusions of this article is available upon reasonable request from the corresponding author. Informed consent was obtained from all participants prior to data collection. All respondents were assured of anonymity and the voluntary nature of their participation.



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APPENDIX A: SURVEY INSTRUMENT

Table A1 presents all 20 measurement items, their original sources, and their final PLS-SEM indicator loadings. All items were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Arabic translation followed the translation-back-translation procedure with bilingual expert panel consensus.

Table A1 — Measurement items, sources, and indicator loadings

Code	Construct	Item Text	Source	Loading
DTI1	DTI	Our university invests significantly in AI systems and intelligent platforms to support teaching and research.	Ghosh et al. (2024)	0.851
DTI2		Our university maintains advanced cloud computing and cybersecurity infrastructure.	Alamri et al. (2023)	0.878
DTI3		Our university provides dedicated budgets for digital skills development and staff technology training.	Ghosh et al. (2024)	0.824
DTI4		Our university continuously upgrades its digital infrastructure to remain technologically competitive.	Akram, Khan, and Malik (2025)	0.798
EDT1	EdTech	Our university's LMS is deeply integrated into routine teaching, assessment, and administrative practice.	Kim et al. (2024)	0.891
EDT2		Faculty actively use adaptive learning platforms and AI-supported digital pedagogical tools.	Aboagye et al. (2025)	0.867
EDT3		Mobile learning environments are accessible and widely used by students and staff.	Kim et al. (2024)	0.856
EDT4		Digital pedagogy development is systematically supported through faculty training and institutional policy.	Aboagye et al. (2025)	0.912
QA1	QA	Our quality monitoring systems are fully digitised and use data analytics for continuous improvement.	Munoz and Harb (2024)	0.836
QA2		Accreditation processes incorporate digital competency standards and EdTech utilisation criteria.	Shamsi (2024)	0.798
QA3		QA feedback mechanisms use analytics to identify improvement opportunities in teaching and research.	Munoz and Harb (2024)	0.856
QA4		Our QA framework is strategically aligned with digital transformation and innovation objectives.	Hussein and El-Naggar (2025)	0.736
IC1	IC	Our institution supports innovation hubs, technology transfer offices, and research commercialisation.	Vidicki, Vrgović, Stevanov, and Medić (2023)	0.901
IC2		Faculty regularly participate in knowledge transfer, industry partnerships, and applied research.	Vidicki et al. (2023)	0.856

Code	Construct	Item Text	Source	Loading
IC3		Student-led innovation projects are systematically supported through institutional programmes.	Centobelli, Cerchione, and Esposito (2019)	0.878
IC4		Our institution has a track record of research outputs with commercial or societal application.	Vidicki et al. (2023)	0.768
EUC1	EUC	Our institution has formal structures for student/faculty entrepreneurship including incubators.	Abreu and Grinevich (2024)	0.889
EUC2		Our institution maintains active partnerships with industry, NGOs, and government for knowledge exchange.	Costa, Fernandes, and Neves (2025)	0.867
EUC3		Entrepreneurship and innovation are integrated into the curriculum across multiple disciplines.	Abreu and Grinevich (2024)	0.853
EUC4		Our institution has a visible innovation/entrepreneurship centre with measurable third-mission outcomes.	Costa et al. (2025)	0.753

Note: All loadings from final PLS-SEM measurement model (SmartPLS 4; N=360). All loadings exceed 0.70 threshold (Hair et al., 2022). Pilot Cronbach's α (n = 50): DTI = 0.83; EdTech = 0.86; QA = 0.81; IC = 0.87; EUC = 0.85

Employees' Perceived Strategic Interrelatedness Between Sustainability and Quality Management: A Cross-Sectional Multi-Sector Study in Türkiye

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Omer Ozkan, Nezih Metin Özmutaf

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ABSTRACT

Purpose: To examine employees' perceptions of the strategic importance and perceived interrelatedness of sustainability and quality management within a cross-sectional multi-sector sample in Türkiye.

Methodology/Approach: A quantitative, cross-sectional survey design was employed using a structured questionnaire administered to 253 employees from eight sector categories. The data were analysed through exploratory factor analysis, one-sample t-tests, and structural equation modelling (SEM) using SPSS and AMOS.

Findings: Respondents attached high strategic importance to both sustainability and quality management dimensions. The SEM results suggest a statistically significant but weak positive association between the perceived strategic importance of sustainability and the perceived strategic importance of quality management.

Research Limitation/Implication: The study is limited to cross-sectional, self-reported survey data collected from 253 employees across eight sector categories in Türkiye.

Originality/Value of paper: The study contributes by proposing and empirically examining a perception-based instrument that links sustainability and quality management within a Turkish multi-sector context, thereby complementing integrated-management-system, EFQM, ISO, and TQM-oriented studies with employee-level evidence on perceived strategic interrelatedness.

Category: Research paper

Keywords: sustainability; quality management; organizations; strategic context

Research Areas: Quality by Sustainability; Strategic Quality Management

1 INTRODUCTION

Organizations operate under conditions of limited resources while striving, on the one hand, to strategically meet the expectations of customers, society, stakeholders, and the environment through value creation, and on the other hand, to achieve balanced growth and development by sustaining competitive advantage in an increasingly competitive environment. Accordingly, organizations pursue their activities within the scope of their missions in interaction with both their internal and external environments, enabling them to achieve their objectives and goals and, consequently, to ensure sustainability.

In recent years, leading organizations and governments worldwide have increasingly recognized sustainability – both social and environmental – as one of the foremost strategic priorities. This strategic orientation has the potential to make a significant contribution to the long-term maintenance and advancement of sustainability (Oakland, 2014, p. 77).

On the other hand, organizations implement a certain level of quality standardization across all managerial processes, including pre-production, production, sales/service delivery, and post-sales/service activities. Within this framework, organizations operate with a strong emphasis on value creation throughout their quality management processes.

Both sustainability and quality management should be regarded not as outcomes, but as continuous and never-ending processes embedded within a strategic context. Accordingly, organizations are expected to evaluate the achievement of sustainability and the implementation of quality management not only separately but also in interaction with one another, across the short, medium, long, and very long term from a strategic perspective. In line with this objective, the present study examines employees' perceptions of the strategic importance of sustainability and quality management within organizations, as well as the perceived interrelatedness between these two concepts.

2 LITERATURE REVIEW

2.1 Sustainability

In the Our Common Future report published by the World Commission on Environment and Development (WCED), sustainability is addressed within a normative and strategic framework based on the principle of intergenerational equity (WCED, 1987, p. 41). Accordingly, the concept of sustainability encompasses not only environmental and ethical concerns but also social and economic dimensions.

Elkington (1997, p. 70), through the triple bottom line approach, conceptualizes sustainability as an interactive framework consisting of economic, environmental, and social dimensions. From an organizational perspective, this approach may

systematically form an integrated structure that creates value within the concept of quality from the viewpoint of customers and target groups, while simultaneously constituting the foundation for long-term competitive advantage.

Sustainability can also be considered synonymous with strategic orientation for organizations. Strategic management represents an effort to holistically address organizations' past, present, and future (short-, medium-, long-, and very long-term) in conjunction with external environmental conditions. Within the shared value approach proposed by Porter & Kramer (2011, p. 64), it is emphasized that making positive contributions to the resolution of social and environmental problems can generate strategic opportunities for organizations and lead to competitive advantage. Similarly, Eccles, Ioannou, & Serafeim (2014) demonstrate that sustainability-oriented management practices developed within a strategic context maximize long-term financial and operational performance. From this perspective, profitability should not be viewed as an objective in itself, but rather as an outcome of a process embedded in sustainability-driven efforts.

The Sustainable Development Goals (SDGs), established by the United Nations, provide a globally recognized reference framework for organizations by addressing issues such as enhancing prosperity and peace within an equitable framework, overcoming poverty, protecting the environment, and responding to the climate crisis (United Nations, 2015, p. 3). Within this context, themes such as quality, sustainable production and consumption, and human-centered working conditions are particularly emphasized.

When addressed in an integrated manner from a quality management perspective within the framework of standards, sustainability can contribute to systematic implementation, long-term continuity, and sustained success. Sustainability objectives are strongly grounded in quality standards. In particular, standards such as ISO 14001 and ISO 50001 support the systematic improvement of environmental and energy performance, while ISO 26000 provides a guiding framework for social responsibility (Zeng, Meng, Yin, Tam, & Sun, 2011, p. 978; Lozano et al., 2015, p. 433).

2.2 Quality Management

The concept of quality may be defined as the presence of specific attributes that encompass positive change and transformation as a philosophy, an approach, and a management practice. From the customer perspective, quality can be explained as the ability to meet customer expectations, while from the product and service perspective it refers to possessing the required characteristics and attributes (Kumar, Singh, Kumar, & Antil, 2016, p. 45; Garvin, 1987, p. 104). Quality management, within a strategic perspective, may be defined as a management approach and philosophy that incorporates leadership, customer focus, process orientation, human resources, continuous improvement, learning, and innovation (Knowles, 2011, pp. 11–12). From another perspective, quality management, in technical terms, encompasses a set of principles, practices, and techniques aimed

at improving organizational performance, which inherently include process control mechanisms and behavioural practices (Dean & Bowen, 1994, pp. 395–396).

The historical development of quality management reveals a progressive evolution from inspection, to process and system control, to total quality control, and ultimately to total quality management, which emphasizes the quality of all managerial processes in an integrated manner (Garvin, 1988, pp. 18–25). The contemporary understanding of quality management has been significantly shaped by pioneering contributors such as W. E. Deming (1986; post 1945 PDCA cycle, 14 principles of quality, participative culture), J. M. Juran (1988, 1950s; managerial processes, leadership), K. Ishikawa (1950s; Ishikawa diagram, quality circles), G. Taguchi (1960s; quality standards and loss function), V. Feigenbaum (1970s; Total Quality Control), P. B. Crosby (1979, 1970s; conformance to requirements), and T. Peters and R. H. Waterman (1980s; excellence and quality culture) (Luthra, Dixit, Agarwal, & Mangla, 2021, p. 12; Dale, 1999, p. 21; Chileshe, 2007, p. 52).

Within this framework, quality management can be regarded as a comprehensive management approach and/or philosophy that encompasses leadership and motivation, participation, continuous improvement, continuous education and training, internal and external customer orientation, process management and standardization, as well as sensitivity to external environments and conditions.

Within this framework, the continuous improvement (Kaizen) approach pioneered by Masaaki Imai is grounded in the sustainable development of quality across all sectors, fields, and activities, with a particular emphasis on improvement and advancement for societal benefit. In this approach, quality is brought to a certain standard, practices continue, and subsequently a new standard is established; this process proceeds in an ongoing and never-ending manner. The continuous improvement cycle is supported by organizational culture, effective leadership, education and training, and the application of problem-solving techniques (Imai, 1986, p. 95).

The development of quality and quality management has been supported and advanced through specific standards. In this regard, the ISO 9001 standard has played a central and highly significant role in the institutionalization of quality management at the international level. With the ISO 9001:2015 revision, elements such as strategic management, risk-based thinking, and stakeholder expectations have become integral components of quality management systems (ISO, 2015, p. 8). Empirical studies demonstrate that ISO 9001 implementation has positive and lasting effects on operational efficiency, reduction of error rates, and improvements in both internal and external customer satisfaction (Benner & Veloso, 2008; Psomas, Fotopoulos, & Kafetzopoulos, 2013, p. 670).

Another important approach contributing to quality standardization and practical implementation is the EFQM Excellence Model. The EFQM Excellence Model is based on a journey toward excellence in quality and the sustained efforts required to achieve it. The model addresses quality in an integrated manner through

leadership, strategy, people, processes, and societal results, and presents organizations with a long-term excellence perspective structured across defined dimensions with specific weightings (EFQM, 2020, p. 9). A critical point to note, however, is that the model goes beyond internal efficiency and value creation by promoting a win-win strategy that delivers both societal and environmental benefits (EFQM, 2020, p. 6).

In recent years, digitalization and data-driven management approaches have further expanded the scope of quality management. Big data analytics, process mining, and artificial intelligence-supported decision-making mechanisms are transforming quality management into a more predictive and proactive structure (Antony et al., 2021, p. 560). In this context, key elements in the development of sustainable quality include artificial intelligence applications, communication and high-performance technologies, predictive analytics (e.g., classification and regression), clustering and accumulation (e.g., descriptive analytics), as well as data storage and data cleansing processes (Akpınar, 2000, p. 2). For example, leveraging the opportunities provided by big data, organizations are creating numerous sustainability clusters aligned with business innovation, while transforming operational patterns to generate environmental benefits (Etzion & Aragón-Correa, 2016, p. 7). These developments clearly demonstrate that quality management functions as a strategic lever for sustainability across all domains and processes.

2.3. The Relationship Between Sustainability and Quality Management

In organizations, both quality management and sustainability – together with their underlying philosophies, approaches, and practices – constitute an integrated set of processes that generate solutions to ensure sustainability and are realized through leadership ownership and guidance. In this regard, the presence of strong leadership capabilities and supportive managerial commitment plays a fundamental role (Oakland, 2014, pp. 43–45, 77).

Accordingly, the existence of an appropriate organizational culture and climate that supports both sustainability and quality management within a leadership framework is indispensable. From this perspective, sustainability and quality should be shared and internalized as a coherent set of organizational values, serving a guiding function across the organization. When quality is addressed holistically, it has the potential to lead organizations toward successful outcomes. Therefore, it can be argued that a sustainability and quality management approach that proactively considers both internal and external environments from a strategic perspective is inevitable (Al-Ani & Al-Mashhadani, 2004, p. 350).

When referring to the external environment, priority is given to nature, well-being, society, individuals, organizations, as well as the immediate and broader external organizational environment and its components, together with the sustainable fulfilment of their needs and expectations (Boaden, 1997, p. 161). For both organizations and all segments of society, attributes such as legitimacy, openness, transparency, clarity, credibility, respect, ethics, trust, a human-centered

orientation, innovativeness, and social usefulness are indispensable in ensuring comprehensibility and acceptance. All levels of management are obliged and responsible for adopting a participatory approach to quality management for sustainability, including actively soliciting the views and expectations of society and citizens (Boyne, Gould-Williams, Law, & Walker, 2002, p. 13).

Boyne et al. (2002, p. 10) define quality management as a performance improvement strategy that encompasses improvement-oriented approaches from an organizational perspective, revealing how an organization actually operates. Notably, this perspective does not emphasize profitability or self-interest. In fact, within the framework of contemporary management understanding, neither product nor service provision is pursued solely for profitability. Rather, profitability can be considered a natural outcome that emerges from the successful implementation of sustainability-oriented quality management.

Quality management implies the existence of an integrative infrastructure that connects operational processes down to their finest details. From a process-oriented perspective, this framework enables sustainability to move beyond an abstract vision and be transformed into measurable performance indicators (Zairi, 2002, p. 1163).

On the other hand, empirical research demonstrates that organizations that effectively implement quality management systems achieve superior outcomes in areas such as environmental performance, occupational health and safety, and social responsibility (Heras-Saizarbitoria, Molina-Azorín, & Dick, 2011, p. 6; Siva et al., 2016, p. 151). Within the context of standardization, the integration of ISO 9001 and ISO 14001 systems enhances cost efficiency while enabling the systematic management of environmental risks (Bernardo, Simon, Tarí, & Molina-Azorín, 2015, p. 264).

From a sustainability perspective, quality management also plays a critical role in supply chain management and stakeholder relations. Sustainable supply chain practices are disseminated through quality standards and contribute to controlling environmental and social risks throughout the entire supply chain (Seuring & Müller, 2008, p. 1702).

This situation reveals that quality management functions as an “implementation mechanism” for sustainability. For example, mechanisms that support the objectives and targets of various stakeholder groups, influence and transform suppliers’ practices and behaviours, and provide monitoring and improvement functions bring the philosophy of “total benefit” to the forefront (Bové & Swartz, 2016, p. 7).

Moreover, quality management supports the consistent and systematic management of sustainable innovation. A culture of continuous improvement provides a fertile ground for the development of innovative solutions in areas such as environmental efficiency, resource effectiveness, and social innovation (Boiral, Heras-Saizarbitoria, & Testa, 2018). With digital transformation, quality

management enables the real-time monitoring of sustainability performance and facilitates more agile management practices. In this context, the relationship between sustainability and quality management should be viewed not as linear, but as a mutually reinforcing, dynamic, and strategically embedded interaction.

Furthermore, within the stakeholder framework, quality and sustainability are increasingly regarded as integral components of overall quality of life. In practice, successful innovation processes tend to emerge alongside effective quality management and sustainability practices. Within the framework of innovation, quality, and sustainability, it becomes possible to achieve higher levels of value through effective design, lower costs and resource utilization, and enhanced overall benefits (Trott, 2017, pp. 58, 127, 168).

3 RESEARCH

3.1 Research Objective

The primary objective of this research is to examine employees' perceptions of the strategic importance of sustainability and quality management and to test the perceived interrelatedness between these two constructs. The study therefore addresses a perception-based empirical question rather than measuring implemented practices, management-system integration, sustainability performance, or organizational outcomes.

3.2 Data Collection Instruments

The data collection instrument used in this study consists of two main sections. The first section includes the independent variables of the research, namely age, gender, educational level, position (managerial or non-managerial), sector, and length of professional experience. In addition, participants' overall perceptions of sustainability and quality management within a strategic framework were assessed through the question: "To what extent are sustainability and quality management related?"

The second section presents the core strategic framework for sustainability and quality management in organizations within a two-dimensional structure. In this context, the scale comprises 15 items related to sustainability and 10 items related to quality management. At the strategic level, the sustainability dimension is primarily grounded in Freeman's (1984) stakeholder-based strategic management approach and the long-term sustainable value creation perspective proposed by Bansal and DesJardine (2014). The quality management dimension is mainly based on the quality management and continuous improvement approaches developed by Juran (1988) and Deming (1986).

For statistical analysis, all items were measured using a five-point Likert scale, where 1 = strongly disagree, 2 = disagree, 3 = moderately agree, 4 = agree, and 5 = strongly agree.

3.3 Data Collection and Analysis

The questionnaires were administered to a total of 253 employees working in eight sector categories, namely energy, consulting, education, healthcare, services, manufacturing, public sector, and information technology, between June 2025 and December 2025. Factor analysis, one-sample t-tests, and structural equation modelling (SEM) were employed as the main analytical techniques. Statistical analyses were conducted using SPSS and AMOS, and the findings were interpreted in light of the relevant literature. Because the data are cross-sectional and self-reported, the results are interpreted as perception-based associations rather than causal effects.

A non-probability convenience sampling approach was employed in this study. Participants were recruited through professional networks and organizational contacts operating in different sectors in Türkiye. Participation was voluntary and anonymous. Only fully completed questionnaires were included in the final analysis, resulting in an analysable sample of 253 respondents. Due to the non-probability nature of the sampling process, the findings should be interpreted as perception-based evidence derived from the observed sample rather than as statistically representative findings for all organizations or sectors.

Questionnaire development and validation. The instrument comprised 25 Likert-type items: 15 sustainability-related items and 10 quality-management-related items. The items were designed to operationalize the conceptual framework derived from the literature and were examined through factor analysis.

To reduce the risk of common method bias, procedural remedies were implemented during data collection. Participants were informed that responses would remain anonymous and be used only for scientific purposes, thereby reducing evaluation apprehension and social desirability bias. In addition, all questionnaire items were presented using standardized response categories and neutral wording.

The study was conducted in accordance with the principles of voluntary participation, confidentiality, and informed consent. No personal or sensitive data were collected. Participants were informed about the purpose of the study prior to participation and consented to the use of their responses for academic research.

Effect sizes and statistical significance were interpreted jointly to avoid overreliance on p-values. Given the cross-sectional and self-reported nature of the data, the findings should be interpreted as perception-based associations rather than causal relationships.

The authors declare that no external funding was received for this research and that there are no conflicts of interest associated with the study. The dataset supporting

the findings of this study is available from the corresponding author upon reasonable request. Statistical analyses were conducted using SPSS and AMOS, and analysis outputs were retained to ensure transparency and reproducibility.

3.4 Research Hypotheses

The main hypotheses of the study are formulated as follows:

H1: Within the strategic context of organizations, the quality management framework factors are perceived as important (f1: Human resources, production and value creation; f5: Leadership, value creation, and holistic integration).

H2: Within the strategic context of organizations, the sustainability framework factors are perceived as important (f2: Leadership and value creation; f3: Well-being and nature; f4: Proactiveness and clarity; f6: Culture and strategy).

H3: There is a positive association between employees' perceived strategic importance of sustainability and employees' perceived strategic importance of quality management.

4 FINDINGS

4.1 Findings Related to Participants

The mean age of the participants included in the study ($n = 253$) was 46.0 ± 9.26 years (min–max = 27–70). The mean age was 46.1 ± 9.96 years for female participants ($n = 109$, 43.1%) and 45.9 ± 8.73 years for male participants ($n = 144$, 56.9%). Regarding educational level, 49% of the participants held a bachelor's degree ($n = 124$), while 51% held a postgraduate degree ($n = 129$). In terms of professional experience, 17.0% of the participants had 1–9 years of experience ($n = 43$), whereas 83.0% had 10 years or more of professional experience ($n = 210$). With respect to organizational position, 62.1% of the participants were managers ($n = 157$), while 37.9% were non-managerial employees ($n = 96$).

The participants represented a broad sectoral distribution across eight categories. However, because the study does not rely on probability sampling, the findings should be interpreted as analytically informative for the observed sample rather than statistically representative of all sectors. Participation was relatively higher in the manufacturing, services, and healthcare sectors, respectively (see Table 1).

Table 1 – Sector (field) of participants

Sector (Field)	n	%
Energy	26	10.3
Consulting	28	11.1
Education	20	7.9

Sector (Field)	n	%
Healthcare	33	13.0
Services	41	16.2
Manufacturing	69	27.3
Public Sector	13	5.1
Information Technology (IT)	23	9.1
Total	253	100.0

Participants' overall perceptions regarding the interrelatedness of sustainability and quality management within a strategic context are presented in Table 2. The vast majority of participants perceive this interrelationship to be at a high or very high level. Only 4.3% of the participants ($n = 11$) reported that the relationship is at a moderate level. Accordingly, based on these results, none of the respondents – despite representing different sectors – perceived the relationship between sustainability and quality management as insignificant (see Table 2).

Table 2 – Sustainability and quality management

Level	n	%
Moderate	11	4.3
High	109	43.1
Very High	133	52.6
Total	253	100.0

4.2 Validity and Reliability of the Measurement Instruments

In the second section of the questionnaire, Principal Component Analysis (PCA) was applied as the extraction method within the framework of Exploratory Factor Analysis (EFA) to examine the items related to sustainability and quality management in a strategic context. Varimax rotation (orthogonal rotation) was employed as the rotation method. This orthogonal rotation facilitated a clearer and more interpretable factor structure, thereby yielding a parsimonious solution.

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.819, and Bartlett's Test of Sphericity yielded a statistically significant result ($\chi^2 = 4011.569$, $df = 300$, $p < 0.001$). The diagonal values of the anti-image correlation matrix ranged from 0.775 to 0.891. Based on these findings, the data were considered suitable for factor analysis. Furthermore, no items were removed from the six-factor solution (Tables 3 and Table 4).

For the construction of factor scores, the arithmetic means of the items comprising each factor were calculated. This approach provided continuous measurement

variables representing each factor, which were subsequently used in the statistical analyses.

The resulting six-factor structure explained 70.736% of the total variance. Specifically, the first factor accounted for 20.681%, the second factor 11.831%, the third factor 11.168%, the fourth factor 10.155%, the fifth factor 9.731%, and the sixth factor 7.169% of the total variance. The overall Cronbach's alpha coefficient for the six-factor structure was 0.951, indicating a high level of internal consistency. The overall item mean was 4.248, with a variance of 0.523. These results demonstrate that the factors represented by the items in the questionnaire explain the construct at a high and reliable level (see Table 3).

The extracted factors were labelled in accordance with the content of their respective items as follows: f1: Human resources, production and value creation; f2: Leadership and value creation; f3: Well-being and nature; f4: Proactiveness and clarity; f5: Leadership, value creation, and holistic integration; and f6: Culture and strategy (see Table 3). Among these factors, f1 and f5 pertain to quality management, whereas f2, f3, f4, and f6 fall within the scope of sustainability.

Table 3 – Validity and reliability test results

Items (Statements)	Factors						Cronbach Alfa
	Human Resources, Production and Value (F1)	Leadership and Value Creation (F2)	Well- Being and Nature (F3)	Proactiveness and Clarity (F4)	Leadership, Value Creation and Holistic Integration (F5)	Culture and Strategy (F6)	General = 0.951
In quality management, ... is of strategic importance as a fundamental element.							
Adopting a participatory management approach within a quality-oriented framework	0.878	0.043	-0.015	-0.063	0.043	0.175	0.909
Ensuring the most efficient use of scarce resources (labour, natural resources, capital, knowledge, etc.)	0.863	0.060	-0.025	-0.002	0.010	0.182	0.913
Enhancing employees' work and overall quality of life in a holistic manner	0.826	0.042	0.115	0.083	0.251	-0.117	0.907

Items (Statements)	Factors						Cronbach Alfa
	Human Resources, Production and Value (F1)	Leadership and Value Creation (F2)	Well- Being and Nature (F3)	Proactiveness and Clarity (F4)	Leadership, Value Creation and Holistic Integration (F5)	Culture and Strategy (F6)	General = 0.951
Mobilizing efforts and opportunities to support employees' continuous development	0.797	0.069	0.102	0.057	0.321	-0.072	0.908
Maintaining the highest quality standards across pre-production, production, sales, and after-sales processes	0.789	0.024	0.041	0.036	0.296	-0.048	0.911
Valuing people, human-centered values, and individual potential (e.g., innovativeness, ethics, dignity)	0.754	0.025	-0.045	0.154	0.066	-0.070	0.915
Undertaking initiatives to enhance corporate, societal, and individual customer orientation, expectations, and satisfaction	0.694	0,069	-0,014	-0,038	0,457	0,001	0,916
0.924							
In sustainability, ... is of strategic importance as a fundamental element.							
Effective and efficient use of resources	0.120	0.792	0.077	0.202	0.066	0.168	0.699
Projects, activities, and contributions that generate value for society	0.015	0.741	0.246	0.165	0.137	-0.216	0.755
Alignment of stakeholder engagement with a win-win strategy	0.047	0.703	0.263	0.271	-0.029	0.075	0.706

Items (Statements)	Factors						Cronbach Alfa
	Human Resources, Production and Value (F1)	Leadership and Value Creation (F2)	Well- Being and Nature (F3)	Proactiveness and Clarity (F4)	Leadership, Value Creation and Holistic Integration (F5)	Culture and Strategy (F6)	General = 0.951
Leadership's vision, commitment, and guiding role	0.047	0.533	-0.201	0.528	-0.034	0.224	0.790
Approaches, activities, and contributions aimed at enhancing well-being	0.067	-0.185	0.806	0.234	-0.035	0.078	0.721
Ensuring the continuity of natural systems and resources for future generations within a framework of balance and moderation	0.030	0.212	0.687	-0.003	-0.093	0.276	0.725
Meeting and managing stakeholders' expectations	-0.094	0.257	0.667	0.143	0.004	-0.148	0.767
The presence of social equality, justice, and democratic principles	-0.036	0.337	0.592	0.142	-0.003	0.433	0.721
Achieving growth and profitability within a holistic framework integrated with service to society	0.216	0.454	0.527	0.171	0.151	0.082	0.752
Demonstrating proactive and strategic behaviours to ensure sustainability	0.059	0.107	0.119	0.842	-0.022	0.033	0.711
Exhibiting responsible, transparent, and clearly articulated orientations	-0.045	0.415	0.153	0.656	0.035	-0.126	0.733
Employee satisfaction and continuous development	0.114	0.254	0.241	0.632	-0.006	0.211	0.734

Items (Statements)	Factors						Cronbach Alfa
	Human Resources, Production and Value (F1)	Leadership and Value Creation (F2)	Well- Being and Nature (F3)	Proactiveness and Clarity (F4)	Leadership, Value Creation and Holistic Integration (F5)	Culture and Strategy (F6)	General = 0.951
Placing people and human-centered values at the core	0.045	0.114	0.489	0.602	0.027	0.093	0.742
0.783							
In quality management, ... is of strategic importance as a fundamental element.							
Being under the responsibility of top management and its leadership	0.318	0.034	-0.060	0.016	0.885	0.073	0.771
Viewing image, reputation, and profitability as outcomes of the delivery of quality	0.384	-0.011	0.008	0.030	0.858	0.009	0.766
Adopting a holistic orientation toward quality through preventive and continuous improvement approaches	0.468	0.255	-0.021	-0.090	0.602	0.146	0.739
0.797							
In sustainability, ... is of strategic importance as a fundamental element.							
Developing organizational culture to support sustainability and transforming it when necessary	0.224	0.320	0.164	0.037	0.056	0.707	-
Placing sustainability at the core through a strategic perspective	-0.211	-0.301	0.168	0.205	0.138	0.653	-
0.691							

As shown in Table 3, the six-factor solution demonstrated high overall internal consistency. The communalities of the retained items are presented in Table 4, indicating the proportion of variance in each item accounted for by the extracted factor solution.

Table 4 – Communalities

	Initial	Extraction
Placing sustainability at the center through a strategic perspective	1.000	0.651
Developing organizational culture for sustainability and transforming it when necessary	1.000	0.684
Leadership's pioneering role, commitment, and guidance	1.000	0.657
Demonstrating proactive strategic behaviours for sustainability	1.000	0.740
Demonstrating responsible, open, transparent, and clearly articulated orientations	1.000	0.644
Alignment of stakeholder engagement with a win-win strategy	1.000	0.646
Effective use of resources	1.000	0.721
Placing people and human-centered elements at the core	1.000	0.626
Employee satisfaction and development	1.000	0.579
The existence of social equality, justice, and democratic principles	1.000	0.673
All types of projects, activities, and contributions that can be made to society	1.000	0.703
Ensuring that natural systems and resources can be carried into the future within a framework of balance and moderation	1.000	0.602
Meeting stakeholders' expectations	1.000	0.562
Approaches, activities, and contributions aimed at increasing well-being	1.000	0.751
Achieving growth and profitability within a holistic framework integrated with service to society	1.000	0.589
Placing sustainability at the center through a strategic perspective	1.000	0.894
Developing organizational culture for sustainability and transforming it when necessary	1.000	0.782
Leadership's pioneering role, commitment, and guidance	1.000	0.696
Demonstrating proactive strategic behaviours for sustainability	1.000	0.716
Being under the responsibility of top management and its leadership	1.000	0.604
Ensuring the most efficient use of scarce resources (labour, natural resources, capital, knowledge, etc.)	1.000	0.781
Activities aimed at increasing organizational, societal, and individual customer orientation, expectations, and satisfaction	1.000	0.761
Not compromising the highest quality standards in pre-production, production, sales, and after-sales processes	1.000	0.677
Valuing people, human values, and human potential (innovativeness, ethics, dignity, etc.)	1.000	0.884
Increasing employees' work and private-life quality in a holistic manner	1.000	0.809
Extraction Method: Principal Component Analysis.		

4.3 Findings Related to the Factors

The main hypotheses of the study, H1 (quality-management-related factors are perceived as important) and H2 (sustainability-related factors are perceived as important), were supported for all relevant factors. Accordingly, the propositions were statistically significant, indicating that participants attached a high level of strategic importance to each factor separately within the quality management and sustainability frameworks (Table 5).

Table 5 – One-sample t-test

Factors	n	$\bar{x} \pm s$	Test Value = 3	
			t	p
Human Resources, Production and Value (k1)	253	4.2 $\pm$ 0.55	35.357	p < 0.001
Leadership and Value Creation (s1)	253	4.1 $\pm$ 0.65	28.674	p < 0.001
Well-Being and Nature (s2)	253	4.2 $\pm$ 0.52	38.645	p < 0.001
Proactiveness and Clarity (s3)	253	4.2 $\pm$ 0.52	38.715	p < 0.001
Leadership, Value Creation, and Holistic Integration (k2)	253	4.3 $\pm$ 0.66	33.418	p < 0.001
Culture and Strategy (s4)	253	4.1 $\pm$ 0.59	29.773	p < 0.001

Note: “s” refers to sustainability-related factors, whereas “k” refers to quality-related factors.

4.4 Structural Equation Modelling

To present the structural equation model (SEM) of the study in a more parsimonious and comprehensible manner, factor means were used to specify sustainability (S) and quality management (K) as latent variables, while the factors were treated as observed variables/indicators. The research model was specified not in terms of sustainability and quality management as dependent and independent variables, but rather in terms of the association between the two latent variables. Maximum Likelihood (ML) was employed as the estimation method.

According to the structural equation model, Hypothesis H3 was supported (Table 6). The estimated covariance path was positive and statistically significant, although the magnitude of the association was weak. Therefore, the finding should be interpreted as evidence of perceived interrelatedness rather than a strong structural effect, causal relationship, or implemented organizational integration. The obtained fit indices (CMIN/DF = 2.652, GFI = 0.974, NFI = 0.945, CFI = 0.964, and RMSEA = 0.073) indicate an acceptable to good level of model fit (Figure 1).

In addition, the Average Variance Extracted (AVE) and Composite Reliability (CR) values were calculated. For sustainability, AVE was 0.655875 and CR was 0.876806. For quality management, AVE was 0.878450 and CR was 0.935000.

These values indicate satisfactory internal consistency and convergent validity for the two latent constructs.

Table 6 – Structural equation model analysis results

Relationship	Estimate	Standard Error	Critical Ratio	p	Result
Sustainability (S) ↔ Quality Management (K)	0.043	0.019	2.312	0.021	Supported

The standardized residuals for the specified SEM are presented in Table 7. These residuals provide an additional diagnostic indication of the discrepancies between the observed and model-implied covariance structures.

Table 7 – Standardized residuals

	k2	k1	s4	s3	s2	s1
k2	0.000					
k1	0.000	0.000				
s4	1.376	0.372	0.000			
s3	-0.769	-0.284	-0.453	0.000		
s2	-0.281	-0.250	1.955	-0.119	0.000	
s1	1.136	0.589	-1.062	0.261	-0.277	0.000

As shown in Table 7, the standardized residuals ranged from -1.062 to 1.955. Reliability and convergent validity results for the two latent constructs are summarized in Table 8.

Table 8 – Reliability and convergent validity of latent constructs

Latent construct	AVE	CR	Assessment
Sustainability (S)	0.655875	0.876806	Satisfactory
Quality Management (K)	0.878450	0.935000	Satisfactory

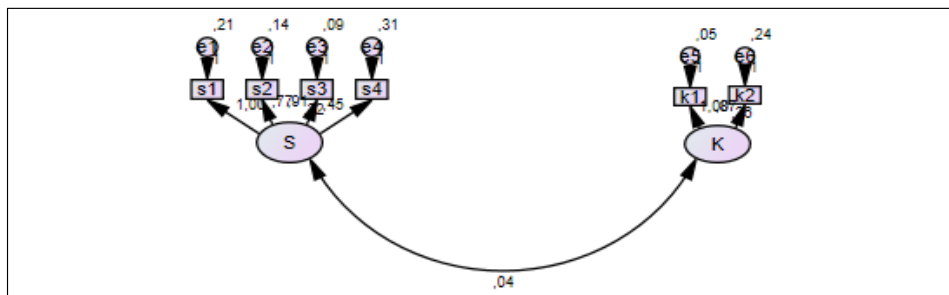


Figure 1 – Structural equation model of the relationship between the strategic importance of sustainability and the strategic importance of quality management

As reported in Table 8, the AVE and CR values were satisfactory for both sustainability and quality management. For completeness, the correlations among the model parameter estimates are presented in Table 9.

Table 9 – Correlations of estimates for the model

	par_1	par_2	par_3	par_4	par_5	par_6	par_7	par_8	par_9	par_10
par_1	1.000									
par_2	0.500	1.000								
par_3	0.260	0.288	1.000							
par_4	0.000	0.000	0.000	1.000						
par_5	-0.122	-0.154	-0.067	-0.134	1.000					
par_6	-0.598	-0.710	-0.326	0.000	0.255	1.000				
par_7	0.000	0.000	0.000	-0.967	0.175	0.03	1.000			

5 DISCUSSION

The results should be positioned as employee-level perception evidence that complements, rather than replaces, research on integrated management systems, EFQM-based excellence models, ISO-based management systems, and TQM-oriented sustainability practices. The empirical contribution lies in validating a perception-based framework in a Turkish multi-sector context and showing that sustainability-related and quality-management-related strategic perceptions are positively associated.

Managerial implications should therefore remain bounded by the evidence. The findings suggest that managers may benefit from communicating sustainability and quality management as mutually supportive strategic priorities, but the data do not demonstrate improvements in competitiveness, leadership effectiveness, sustainability performance, or organizational success. Such effects require additional performance indicators and longitudinal or multi-source research designs.

6 CONCLUSION

This study examined employees' perceived strategic importance of sustainability and quality management and the perceived association between these two constructs. The findings indicate that respondents attributed high importance to the selected sustainability and quality-management dimensions and that these two perception-based constructs were positively, although weakly, associated. These results should be interpreted within the limits of the cross-sectional survey design and should not be read as evidence of causal effects, implemented integration, or realized organizational performance outcomes.

Within this framework, the strategic perception, internalization, and integration of this understanding into managerial processes within organizations will naturally begin with, and be sustained through, leadership by management. Leadership exercised by management in this direction simultaneously enables value creation and supports a holistic approach to the subject matter. The findings obtained within the scope of the research also support this line of reasoning, indicating that, from a strategic sustainability perspective, the factors of “leadership and value creation,” and from a quality management perspective, the factors of “leadership, value creation, and holistic integration,” are particularly prominent. Employees participating in the study from various sectors attach a high level of importance to leadership, as well as to value creation and holistic integration.

On the other hand, the culture and foundational elements of organizations shaped together with their initial founders – such as mission, vision, values, beliefs, norms, principles, and tangible artifacts – also constitute a domain that inherently involves sharing and dissemination under the guidance of leadership. Accordingly, when an organization’s culture supports sustainability and the philosophy of quality, human resources, production, and value creation processes can be mobilized in alignment with this framework. The research findings support this perspective, identifying the factors of “culture and strategy” within the context of strategic sustainability, and “human resources, production, and value creation” within the context of quality management. Participants attach a high level of importance to these dimensions.

Finally, within the organizational framework, participants also perceive as highly important the strategic orientation that acts proactively in alignment with the external environment and communicates this orientation clearly, as well as the proactive support of well-being and nature – both internally and externally – for the present and the future. These aspects are reflected in the factors of “proactiveness and clarity” and “well-being and nature,” which are considered highly significant by the participants.

In the strategic context, the SEM results show that employees who attach higher strategic importance to sustainability also tend to attach higher strategic importance to quality management, although the magnitude of this association is weak. Future research should examine this relationship using longitudinal designs, probability-based sampling, organization-level indicators, and additional constructs such as integrated management-system maturity, EFQM deployment, ISO implementation scope, sustainability performance, innovation capability, and quality performance. The possible influence of sectoral heterogeneity should also be tested statistically rather than inferred from pooled descriptive data.

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ABOUT AUTHORS

Ömer Özkan ORCID: 0000-0002-0752-307X (Ö.Ö.) – Ph.D., Quality Management Department, SOCAR Türkiye, İstanbul, Türkiye, e-mail: omerozkan2016@gmail.com.

Nezih Metin Özmutaf ORCID: 0000-0003-1330-409X (N.M.Ö.) – Prof., Faculty of Economics and Administrative Sciences, İzmir Katip Çelebi University, İzmir, Türkiye, e-mail: nezih.metin.ozmutaf@ikc.edu.tr.

AUHOR CONTRIBUTIONS

Conceptualisation, Ö.Ö. and N.M.Ö.; Methodology, Ö.Ö. and N.M.Ö.; Software, Ö.Ö. and N.M.Ö.; Validation, Ö.Ö. and N.M.Ö.; Formal analysis, Ö.Ö. and N.M.Ö.; Investigation, Ö.Ö.; Resources, Ö.Ö. and N.M.Ö.; Data curation, Ö.Ö. and N.M.Ö.; Original draft preparation, Ö.Ö.; Review and editing, Ö.Ö. and N.M.Ö.; Visualisation, Ö.Ö.; Supervision, N.M.Ö. Both authors have read and approved the final version of the manuscript.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest. The funders had no role in the design of the study, in the collection, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

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APPENDIX A – FULL QUESTIONNAIRE ITEMS APPLIED IN THE FACTOR ANALYSIS

Survey Form on Sustainability and Quality Management

The purpose of this survey is to determine, from a strategic perspective and based on employee opinions, the interrelatedness between sustainability and quality management in organizations. Since the questionnaires will be evaluated collectively, no identifying information, whether organizational or personal, is requested from participants. The average completion time is approximately five minutes. Thank you for your participation and contribution to scientific research.

Participant Information

1. Age:	
2. Gender:	1 () Female 2 () Male
3. Educational Level:	1 () Primary / Secondary / High School 2 () Associate Degree / Bachelor's Degree 3 () Postgraduate
4. Position:	1 () Manager 2 () Other
5. Sector You Work In:	
6. Professional Experience (Years):	
7. To what extent are sustainability and quality management related?	5 () Very High 4 () High 3 () Moderate 2 () Low 1 () Very Low

Please mark each statement using the scale below, where 5 is the highest and 1 is the lowest.

Strongly Agree	Agree	No Opinion	Disagree	Strongly Disagree
5	4	3	2	1

In Sustainability, ... is Strategically Important as a Fundamental Element

Statement	5	4	3	2	1
Placing sustainability at the center through a strategic perspective	☐	☐	☐	☐	☐
Developing organizational culture for sustainability and transforming it when necessary	☐	☐	☐	☐	☐
Leadership's pioneering role, commitment, and guidance	☐	☐	☐	☐	☐
Demonstrating proactive strategic behaviors for sustainability	☐	☐	☐	☐	☐
Demonstrating responsible, open, transparent, and clearly articulated orientations	☐	☐	☐	☐	☐
Alignment of stakeholder engagement with a win-win strategy	☐	☐	☐	☐	☐
Effective use of resources	☐	☐	☐	☐	☐
Placing people and human-centered elements at the core	☐	☐	☐	☐	☐
Employee satisfaction and development	☐	☐	☐	☐	☐
The existence of social equality, justice, and democratic principles	☐	☐	☐	☐	☐
All types of projects, activities, and contributions that can be made to society	☐	☐	☐	☐	☐
Ensuring that natural systems and resources can be carried into the future within a framework of balance and moderation	☐	☐	☐	☐	☐

Statement	5	4	3	2	1
Meeting stakeholders' expectations	☐	☐	☐	☐	☐
Approaches, activities, and contributions aimed at increasing well-being	☐	☐	☐	☐	☐
Achieving growth and profitability within a holistic framework integrated with service to society	☐	☐	☐	☐	☐

In Quality Management, ... is Strategically Important as a Fundamental Element

Statement	5	4	3	2	1
Being under the responsibility of top management and its leadership	☐	☐	☐	☐	☐
Ensuring the most efficient use of scarce resources (labor, natural resources, capital, knowledge, etc.)	☐	☐	☐	☐	☐
Activities aimed at increasing organizational, societal, and individual customer orientation, expectations, and satisfaction	☐	☐	☐	☐	☐
Not compromising the highest quality standards in pre-production, production, sales, and after-sales processes	☐	☐	☐	☐	☐
Valuing people, human values, and human potential (innovativeness, ethics, dignity, etc.)	☐	☐	☐	☐	☐
Increasing employees' work and private-life quality in a holistic manner	☐	☐	☐	☐	☐
Mobilizing efforts and opportunities for employees' continuous development	☐	☐	☐	☐	☐
Orientation toward holistic quality through preventive and continuous-improvement approaches	☐	☐	☐	☐	☐
Viewing image, reputation, and profitability as outcomes of delivering quality	☐	☐	☐	☐	☐
Adopting a participative management approach within a quality-oriented framework	☐	☐	☐	☐	☐

Dr. Ömer ÖZKAN e-mail: _____

Comparative Analysis of Work Engagement, Work-Life Balance, and Soft Skills on Employee Performance: A Generational Perspective (Gen Y vs. Gen Z)

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Narudom Torthienchai, Ruedeechanok Rungruangmaitree

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ABSTRACT

Purpose: This study examined levels of work engagement, work–life balance, soft skills, and employee productivity; the relationships among these variables; and how their effects differ across generations.

Methodology/Approach: A quantitative cross-sectional survey of 800 Thai employees used validated Likert-scale questionnaires and using descriptive statistics, correlation, regression, t-tests, ANOVA, and MANCOVA.

Findings: Work–life balance scored highest, work engagement lowest. Work engagement and work–life balance significantly predicted productivity ($p < 0.001$); soft skills did not. Generational differences were significant for engagement, balance, and productivity, but not soft skills.

Research Limitation/Implication: The cross-sectional design, non-probability sampling, and self-reported measures limit causal inference. Findings support strengthening engagement and work–life balance to boost productivity, while soft skills remain valuable for teamwork.

Originality/Value: This study integrates work engagement, work–life balance, and soft skills into one framework explaining productivity among Generation Y (Gen Y) and Generation Z (Gen Z) employees in Thailand, informing generation-specific HR strategies.

Category: Research paper

Keywords: work engagement; work–life balance; soft skills; employee performance; generation Y and Z

Research Areas: Quality of Life; Strategic Quality Management

1 INTRODUCTION

The modern workforce is undergoing transformation due to rapid technological change, demographic transition and changing employee expectations, creating new challenges for organisations that aim to maintain employee commitment and performance. One of the major changes is the increasing presence of the younger generation, particularly Generation Y (Gen Y) and Generation Z (Gen Z), in the global and Thai labour markets. With these two cohorts increasingly taking on operational and service-oriented roles, organisations are pressured to understand how younger employees differ in their work attitudes, motivational drivers, and performance-related behaviours (Dimock, 2019; Schroth, 2019). In this context, work engagement, work-life balance, and soft skills have become core constructs to explain how employees perform in modern workplaces and why generational comparison is important for human resource management (Deloitte, 2023).

Generation Z are generally described as born between 1997 and 2012, and Generation Y as born between 1981 and 1996 (Dimock, 2019). Many scholars have described Gen Z as digital natives whose ways of thinking, communicating and learning are strongly shaped by constant technological immersion (Prensky, 2001; Turner, 2015). This generation has been raised in an environment profoundly influenced by high-speed internet, mobile technologies and social media. Besides their tech savviness, Gen Z is often described as adaptable, inclusive and deeply invested in identity, personal purpose and continuous learning in their careers (Francis & Hoefel, 2018; Parker & Igielnik, 2020). However, Gen Y represents a cohort that largely experienced, rather than was entirely born into, the digital era, yet is widely portrayed as technologically savvy and comfortable with intensive Information and Communication Technology (ICT) use in work contexts. This generation is frequently characterized as valuing collaboration, flexible working arrangements and meaningful, development-oriented tasks, while placing strong emphasis on maintaining a healthy balance between work and personal life, with empirical evidence showing that their job satisfaction and engagement are closely linked to quality of work life and work-life balance (Muskat & Reitsamer, 2020; Riyanto, Riyanto, & Lukertina, 2019).

Demographic evidence backs the growing importance of these two generations. The evidence shows that Gen Z is quickly becoming a sizable group in the workforce; McCrindle Research (McCrindle & Fell, 2020) states that Gen Z will account for 27% of the global workforce by 2025, and 31% by 2030. According to national labour data from Thailand, Gen Z comprised 7.4 million individuals, or 18.3% of the labour force in 2024, and this share is anticipated to increase as older generations retire (Adecco Thailand, 2023; McCrindle & Fell, 2020). Moreover, Gen Y and Gen Z already represent over half of the workforce in Thailand, making them especially significant for organizational research and practice (ManpowerGroup Thailand, 2024). These changes indicate that one cannot separate an understanding of employee performance from the generational characteristics of the workforce itself (Schroth, 2019).

2 METHODOLOGY

This study used a quantitative research design with a cross-sectional approach to analyse the relationship between work engagement, work-life balance, soft skills, and employee productivity. Moreover, the study examined the differences of these variables among Gen Y and Gen Z employees in the Thai workforce. A quantitative approach was deemed suitable for testing hypothesized relationships between predefined variables, comparing mean differences between generational cohorts, and generating empirical evidence from structured survey data.

2.1 Respondents

The target population consisted of Generation Y (1981 – 1996) and Generation Z (1997 – 2012) employees in Thailand. The study was conducted on 800 respondents, the sample comprised 440 Gen Z respondents (20 – 29 years; 55.0 percent) and 360 Gen Y respondents (30 – 45 years; 45.0 percent). The data were collected using online (Google Form) and offline questionnaires. Participation was voluntary and all respondents provided their informed consent before completing the survey.

2.2 Sampling and Data Collection

Data were collected through questionnaire-based surveys administered to employees who met the study criteria. The questionnaire was made available both online and offline to facilitate access and encourage participation. The online version was administered via Google Forms, and the offline version was given to reachable participants in suitable field settings. Before the full survey, the questionnaire was piloted on a small group of respondents to check the clarity of the wording and to test the reliability of the instrument. Some items were refined based on pilot feedback to make them more appropriate for Thai Gen Y and Gen Z employees. Participation in the study was voluntary and data collection was carried out after informing the participants about the study and obtaining their consent to participate. Table 1 presents the demographic profile of the 800 respondents.

Table 1 – Sample demographics (Survey data, N = 800)

Demographic	Category	N	%
Gender	Male	296	37.0%
	Female	504	63.0%
Generation	Gen Z (Age 20 – 29)	440	55.0%
	Gen Y (Age 30 – 45)	360	45.0%
Occupation	Government employee (Thai organisations in public sectors)	461	57.6%
	Self-started business owner	204	25.5%

Demographic	Category	N	%
	Private company employee	120	15.0%
Job Level	Operational staff	424	53.0%
	Executive	205	25.5%
	Supervisor	102	12.8%
Income (THB/mo)	30,001 – 40,000	381	47.6%
	50,001 and above	209	26.1%
	20,001 – 30,000	190	23.8%

2.3 Instrumentation

The research instrument was a structured questionnaire that was developed from existing measures of work–life interface, work engagement, soft skills and job performance and adapted to the Thai employment context for Gen Y and Gen Z respondents. Responses were recorded on a five-point Likert-type scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). Figure 1 illustrates the conceptual framework linking work-life balance, soft skills, and work engagement to employee productivity. The instrument was made up of four constructs:

- Work-Life Balance (X_1) was composed of seven items that measured time management, work from home flexibility, family conflict, co-worker interaction, and work-location autonomy.
- Soft Skills (X_2) included six dimensions, namely initiative–resourcefulness, assertiveness, conflict management, interpersonal communication, decision-making, and integrity.
- Work Engagement (X_3) consisted of three dimensions: vigor, dedication, and absorption, based on Kahn’s work (1990) and the engagement literature.
- Employee Productivity (Y) consisted of six items relating to satisfaction with remote work, motivation, task completion, efficiency, personal standards of performance, and contribution to team goals. In line with the overall focus on employee performance, these productivity items were used as behavioural indicators of individual performance at work.

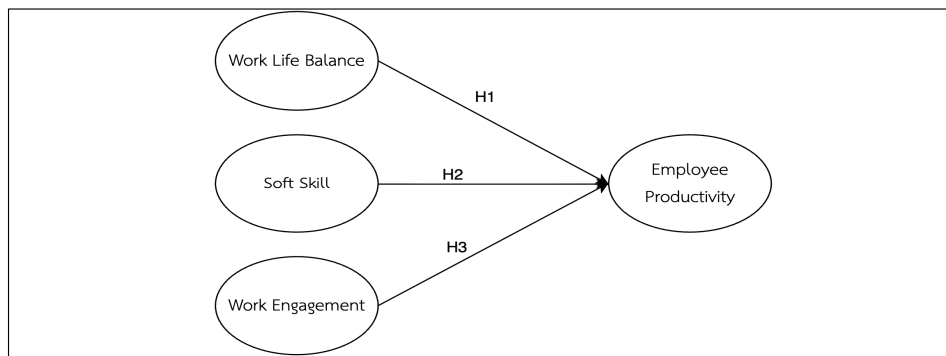


Figure 1 – Conceptual framework

2.4 Data Analysis

Statistical software was used for data analysis. Initially, descriptive statistics were used to summarize the general characteristics of respondents and to describe the distributions of the main study variables. Pearson correlation analysis was used to assess the bivariate relationships between work engagement, work-life balance, soft skills and employee productivity. The test of the predictive effects of the independent variables on the employee productivity was conducted using multiple regression analysis for the whole sample and for the Gen Y and Gen Z groups separately. In addition, independent samples t-tests and MANCOVA were used, when appropriate, to compare the mean levels of work engagement, work-life balance, soft skills and employee productivity between generations. The statistical techniques selected were consistent with the research objectives of examining group differences and estimating the effects of the main explanatory variables on employee productivity.

3 RESULT

This section presents the results of the statistical analyses conducted to address the research objectives. It begins with descriptive statistics to illustrate the levels of work-life balance, soft skills, work engagement, and employee productivity among the respondents. Subsequently, multiple linear regression analysis is employed to examine the effects of work-life balance, soft skills, and work engagement on employee productivity. Finally, generational differences between Generation Y and Generation Z employees are investigated using ANOVA and MANCOVA to determine whether significant differences exist across the study variables. The findings provide empirical evidence regarding the relative importance of each factor in explaining employee productivity and reveal how these relationships vary across different age groups.

Table 2 – Overview of all variables (Survey data, N = 800)

Variable	Mean	Std. Deviation	Level
X1: Work-Life Balance	4.10	0.584	High
X2: Soft Skills	3.85	0.391	High
X3: Work Engagement	3.79	0.550	High
Y: Employee Productivity	3.97	0.572	High

As shown in Table 2, all four variables were rated at a high level by respondents, with Work-Life Balance receiving the highest mean score (4.10) and Work Engagement the lowest (3.79).

Table 3 – Work-life balance (X₁) (Survey data, N = 800)

Item	Mean	Std. Deviation
1. Managing time between work and personal life is not as good as intended	4.22	0.746
2. Can adjust schedule to suit lifestyle when working from home	4.13	0.802
5. Having freedom to choose workplaces positively affects happiness	4.13	0.768
4. Reduced interaction with colleagues since remote work	4.11	0.788
3. Family conflicts have increased since working from home	4.08	0.812
7. Remote work results in encountering work problems	4.02	0.767
6. Remote work has improved work-life balance	3.98	0.776
Overall	4.10	0.584

As presented in Table 3, the highest-rated item was the difficulty in managing time between work and personal life (Mean = 4.22), indicating that respondents, although working from home, still found it challenging to achieve the intended balance. The ability to adjust schedules and freedom of work location were also highly rated (Mean = 4.13), reflecting that flexibility in remote work is perceived as beneficial to personal well-being.

Table 4 – Soft skills (X₂) (Survey data, N = 800)

Dimension	Mean	Std. Deviation
Decision-Making (Maladaptive decision making)	3.95	0.626
Interpersonal Communication	3.91	0.673
Integrity (Ethics)	3.90	0.639
Conflict Management	3.84	0.749
Initiative-Resourcefulness	3.80	0.624

Dimension	Mean	Std. Deviation
Assertiveness	3.72	0.772
Overall	3.85	0.391

Table 4 shows that soft skills were rated at a high level overall (Mean = 3.85). Decision-making received the highest rating (Mean = 3.95), followed by interpersonal communication (Mean = 3.91) and integrity (Mean = 3.90). Assertiveness received the lowest rating among the six dimensions (Mean = 3.72), suggesting this competency may require targeted development.

Table 5 – Work engagement (X_3) (Survey data, $N = 800$)

Dimension	Mean	Std. Deviation
Dedication	3.87	0.528
Absorption	3.77	0.638
Vigor	3.74	0.767
Overall	3.79	0.644

According to Table 5, work engagement was rated at a high level (Mean = 3.79). Dedication – reflecting respondents' sense of self-worth and challenge in their work – was the highest-rated dimension (Mean = 3.87). Vigor, encompassing enthusiasm and motivational drive, received the lowest rating (Mean = 3.74), suggesting that energy and resilience may be areas for organizational support.

Table 6 – Employee productivity (Y) (Survey data, $N = 800$)

Item	Mean	Std. Deviation
1. Satisfied with work during remote work (WFH)	4.14	0.765
2. Motivation decreased when working from home	4.10	0.808
3. Able to accomplish more work when working from home	4.04	0.802
4. Managed work faster and more effectively from home	3.87	0.840
5. Set high personal performance standards	3.83	0.841
6. Always plays a role in driving the team to achieve goals	3.82	0.793
Overall	3.97	0.572

Table 6 indicates that employee productivity was rated at a high level of employee productivity (Mean = 3.97). The highest-rated item was satisfaction with work during remote work (Mean = 4.14), while the lowest-rated item was taking a role in driving team goals (Mean = 3.82). Notably, respondents simultaneously reported high satisfaction with remote work but also acknowledged reduced

motivation while working from home, indicating a nuanced and somewhat paradoxical productivity experience during remote work conditions.

Table 7 – Multiple linear regression: predictors of employee productivity (dependent variable: employee productivity (Y), Survey data, N = 800)

Variable	Mean	Std. Deviation	B (Unstandardized)	t	p-Value
Constant	—	—	0.716	4.101	< 0.001
X ₁ : Work-Life Balance	4.10	0.584	0.231	8.151	< 0.001
X ₂ : Soft Skills	3.85	0.391	0.064	1.184	0.237
X ₃ : Work Engagement	3.79	0.550	0.542	14.523	< 0.001

Table 7 presents the multiple regression results, revealing two statistically significant predictors of employee productivity:

- Work Engagement (X₃) had the strongest influence on employee productivity (B = 0.542, p < 0.001), indicating that for every one-unit increase in work engagement, employee productivity increased by 0.542 units when controlling for other variables.
- Work-Life Balance (X₁) was the second significant predictor (B = 0.231, p < 0.001), affirming that employees who achieve better balance between work demands and personal life demonstrate measurably higher productivity.
- Soft Skills (X₂) did not demonstrate a statistically significant effect on employee productivity (B = 0.064, p = 0.237), suggesting that while soft skills contribute to interpersonal quality and team dynamics, they do not directly predict individual productivity in this sample.

3.1 Generational Comparison: ANOVA Results

Table 8 – Age vs. Work-life balance

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial η^2
Age Group	41.119	6	6.853	23.480	< 0.001	0.151
Error	231.454	793	0.292	—	—	—
Total	272.573	799	—	—	—	—
R ² = 0.151 (Adjusted R ² = 0.144)						

As shown in Table 8, age group significantly influenced work-life balance perceptions (F = 23.480, p < 0.001, η^2 = 0.151). Parameter estimates show that all age groups except ages 20 – 23 (Gen Z early starters) had significantly higher

work-life balance concerns compared to the oldest reference group (ages 43 – 45). Notably, the 30 – 32 age group (early Gen Y) showed the strongest effect ($B = 1.069$, $p < 0.001$). The younger Gen Z group (ages 20 – 23) did not reach statistical significance ($p = 0.067$), likely because this cohort is still in the early stages of their careers after undergraduate graduation.

Table 9 – Age vs. Soft skills

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial η^2
Age Group	1.457	6	0.243	1.595	0.145	0.012
Error	120.743	793	0.152	—	—	—
Total	122.200	799	—	—	—	—
$R^2 = 0.012$ (Adjusted $R^2 = 0.004$)						

Table 9 shows that age group did not significantly influence soft skills perceptions ($F = 1.595$, $p = 0.145$). This finding suggests that soft skills development is driven more by individual experience and personal disposition than by generational membership alone – consistent with the view that emotional maturity is an individual rather than a purely generational characteristic.

Table 10 – Age vs. Work engagement

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial η^2
Age Group	7.423	6	1.237	4.185	< 0.001	0.031
Error	234.441	793	0.296	—	—	—
Total	241.864	799	—	—	—	—
$R^2 = 0.031$ (Adjusted $R^2 = 0.023$)						

As indicated in Table 10, age group significantly influenced work engagement ($F = 4.185$, $p < 0.001$), though the effect size was modest ($\eta^2 = 0.031$). Parameter estimates indicate that the youngest Gen Z group (ages 20 – 23) showed the highest engagement differential compared to the reference group ($B = 0.635$, $p = 0.002$), followed by ages 24 – 26 ($B = 0.663$, $p < 0.001$) and 27 – 29 ($B = 0.648$, $p < 0.001$). Although age group significantly influenced work engagement, the effect size was modest, and the overall pattern across generations showed considerable similarity in engagement attitudes. This was particularly evident among the Gen Y age groups (36 – 39), whose engagement scores clustered around the sample average.

Table 11 shows that age group significantly affected employee productivity ($F = 5.139$, $p < 0.001$), with the early Gen Y cohort (ages 30 – 32) showing the highest productivity differential ($B = 0.757$, $p < 0.001$) and the Gen Z early cohort (ages 20 – 23) also showing a significant effect ($B = 0.714$, $p < 0.001$). Different

age groups demonstrated distinct productivity orientations, reflecting varying career stages, responsibilities, and performance expectations.

Table 11 – Age vs. Employee productivity

Source	Sum of Squares	df	Mean Square	F	Sig.	Partial η^2
Age Group	9.789	6	1.631	5.139	< 0.001	0.037
Error	251.725	793	0.317	—	—	—
Total	261.514	799	—	—	—	—
R ² = 0.037 (Adjusted R ² = 0.030)						

4 CONCLUSION

4.1 Work Engagement as the Primary Driver

In this study, work engagement was the strongest predictor of employee productivity ($B = 0.542$, $p < 0.001$), consistent with previous research by Hanaysha (2016) and Abdelwahed and Al Dohan (2023). The dedication dimension – especially the self-perceived value in the work – was the highest scoring (3.87) of the three engagement sub-dimensions. This implies that employees in both Gen Y and Gen Z groups are significantly more productive when they feel that their work has meaningful value and they have a chance to showcase their skills.

Vigor had the lowest score among the engagement dimensions (Mean = 3.74), and thus, energy-sustaining interventions such as managerial recognition, flexible workload policies, and career development opportunities may be needed to fully activate engagement-productivity linkages, especially for Gen Z workers who are still early in their careers.

4.2 Work-Life Balance as a Significant Contextual Resource

The second major predictor of employee productivity was work-life balance ($B = 0.231$, $p < 0.001$). This finding corresponds to the literature on the double-edged nature of flexible work arrangements as respondents reported high satisfaction with remote work (Mean = 4.14) but reduced motivation when working from home (Mean = 4.10). The highest rated item on the work-life balance scale (Mean = 4.22) was the challenge of managing time between work and personal life, implying that employees need organizational support structures and boundary management tools to fully realize the productivity benefits of flexibility. The significant ANOVA result for age vs. work-life balance ($F = 23.480$, $p < 0.001$, $\eta^2 = 0.151$) (largest effect size of all ANOVA comparisons) reveals that generational membership is a substantial moderator of the experience of work-life balance. In particular, the 30 – 32 age group (early Gen Y) had the highest concern for work-life balance ($B = 1.069$), probably because the group is experiencing

competing demands for career consolidation and family responsibilities at the same time.

4.3 Soft Skills: Significant for Relationships, Not Directly for Productivity

Theoretically, it is interesting that soft skills did not significantly predict employee productivity ($B = 0.064$, $p = 0.237$), which may suggest that soft skills may be necessary for interpersonal quality, team cohesion and relational results (Sumiati & Puspita, 2023), but may be more determinant of productivity at the team level than the individual level in the Thai workforce context. The lack of significant effect of age-group on soft skills ($F = 1.595$, $p = 0.145$) also supports the interpretation that the development of emotional and social skills is an individualized journey, less reliably predicted by generational identity than by personal experience and occupational socialization.

Across the MANCOVA comparisons, three of the four outcome variables – work–life balance, work engagement and employee productivity – were significantly differentiated by age group, whereas soft skills were not. This pattern is consistent with generational theory, which posits that Gen Y and Gen Z differ in how they prioritize work-life integration and what organizational conditions sustain their engagement — but suggests that the personal nature of soft skill development cuts across generational boundaries.

We studied the relationships between work–life balance, soft skills, work engagement, and employee performance, using self-reported productivity as the outcome measure, among Gen Y and Gen Z employees in Thailand ($n = 800$). The main findings are as follows: Work engagement is the most important predictor of employee productivity ($B = 0.542$, $p < 0.001$). With the entry of Gen Z into the workforce, organisations should invest in conditions that encourage dedication, vigor, and absorption. Work-life balance is an important predictor of productivity ($B = 0.231$, $p < 0.001$). Work-life balance differs significantly among age groups ($\eta^2 = 0.151$). Tailored flexibility policies could also serve early-career Gen Z and career-consolidation Gen Y employees. Soft skills do not directly predict individual productivity in this sample ($p = 0.237$), but their value for interpersonal relationships and team dynamics should not be discounted. HR development programmes should position soft skills training as an investment at the team level, not as a lever for individual productivity.

Although there are generational differences in work-life balance, work engagement and productivity perceptions, these are not uniform. The youngest Gen Z group (ages 20-23) showed different patterns than their older Gen Z counterparts. This suggests that career stage and life-stage demands are important contextual moderators. The results provide actionable evidence for HR professionals and organizational leaders seeking to craft engagement strategies, flexibility policies, and talent development programmes that are sensitive to the generational diversity of Thailand's changing workforce.

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ABOUT AUTHORS

Narudom Torthienchai ORCID: 0009-0004-5968-5793 (N.T.) – Assistant Professor, Lecturer of Business School, University of the Thai Chamber of Commerce, Bangkok, Thailand, e-mail: Narudom_tor@utcc.ac.th.

Ruedeethanok Rungruangmaitree ORCID: 0009-0003-3727-5673 (R.R.) – Lecturer of Business School, University of the Thai Chamber of Commerce, Bangkok, Thailand, e-mail: Ruedeethanok_run@utcc.ac.th.

AUTHOR CONTRIBUTIONS

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Conceptualising Individual Innovation Capability in Workplace Settings: A Multidimensional Framework for Future Measurement Development

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Laman Gasimzade

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ABSTRACT

Purpose: This paper proposes a conceptual framework of individual innovation capability (IIC) to guide future measurement development and empirical validation.

Methodology/Approach: An integrative review combined eight Scopus searches and relevant foundational literature. The resulting 44-study corpus was coded across 25 attributes and synthesised through construct-boundary clarification, dimension mapping, conceptual positioning, and relationship mapping.

Findings: IIC is placed between personal innovation resources and innovative work behaviour (IWB), and represented through six candidate capability domains: opportunity exploration, idea generation, idea development, idea mobilisation, idea realisation, and idea sustainment. Organisational and technological conditions are proposed to shape capability development and behavioural enactment.

Research Limitation/Implication: The framework requires operationalisation and empirical validation of its dimensionality, discriminant validity, measurement invariance, and predictive relationships with IWB and innovation outputs.

Originality/Value of paper: The framework distinguishes what employees possess, what they can do, and what they enact at work, providing a conceptual basis for future IIC measurement development.

Category: Conceptual paper

Keywords: individual innovation capability; innovative work behaviour; conceptual framework; scale development; workplace innovation

Research Areas: Management of Technology and Innovation; Quality by Innovation

1 INTRODUCTION

Innovation has become an essential characteristic distinguishing a successful organisation from the ones that fail to adapt to the rapidly modernising technology-dominated business environments. Those who are actively seeking to remain competitive and adapt to uncertainty frequently turn to individuals who can recognise opportunities, produce useful ideas, mobilise support, and convert those ideas into practical improvements. Understanding creativity and innovation at the individual level has therefore been a longstanding concern in organisational research since late 1970-80s as the organisations sought to not only explore who produced the novel and useful ideas, but also which employees could take their ideas one step further leading to their promotion, implementation, and continued use (Amabile, 1983; Anderson, Potočník, & Zhou, 2014). At the organisational level, innovation capability refers to the capacity to generate and implement innovation repeatedly rather than occasionally (Lawson & Samson, 2001).

Existing research on individual-level innovation has identified a range of factors affecting the creative performance in terms of employees' knowledge of the field, operating environment as well as their psychological aptitudes (Amabile, 1983; Amabile & Pratt, 2016). Similarly, how the workplace is set up, the individual characteristics of an employee as well as the approaches exhibited by the leadership staff jointly influence how innovation unfolds at work (Hammond, Neff, Farr, Schwall, & Zhao, 2011). Innovative work behaviour (IWB) research focuses primarily on the enacted innovation-related behaviour covering phases through the generation of idea to its implementation and even sustainability (Scott & Bruce, 1994; Janssen, 2000; Lambriex-Schmitz, Van Der Klink, Beusaert, Bijker, & Segers, 2020). While these models have established multiple approaches for measuring innovation-related behaviour, their dimensions are often fragmented and limited empirical separation exists between these stages. IWB indicates what employees actually do at work, but it does not explicitly distinguish their underlying capability from the organisational and technological opportunities available for its enactment.

This conceptual difficulty becomes more significant as work is increasingly shaped by digital platforms and artificial intelligence, the studies on which have developed multidimensional measures of digital innovation capability and AI-powered service innovation capability at the organisational level (Kroh, Globocnik, Schultz, Holdhof, & Salomo, 2024; Zhou, Zhang, & Wang, 2026). Yet, the framework for individual level capability linking personal resources to enacted IWB remains underrepresented. This paper addresses this gap by proposing a conceptual architecture of individual innovation capability (IIC) and a candidate multidimensional structure for future empirical validation. Personal innovation resources, capability domains, contextual development and activation conditions, and IWB are treated as separate concepts and the paper answers the following question: How should IIC be conceptualised so that it can explain how employees convert personal resources into sustained innovative action under contemporary organisational and technological conditions?

2 CONCEPTUAL BACKGROUND

2.1 Innovation, Creativity, and Innovation Capability

A clear conceptual foundation is crucial because creativity, innovation, innovation capability, individual innovativeness, and IWB refer to related but analytically different aspects of individual innovation. These concepts need to be distinguished analytically to establish the conceptual boundaries allowing for IIC to be developed as a meaningful construct.

Creativity is usually understood as the production of ideas that are both novel and useful. As such the main anchoring theme for creativity is about the generation of original thoughts, approaches, procedures, responses, solutions, or physical products with intrinsic value attached to them. The componential view of creativity suggests that creative performance depends on domain-relevant skills, creativity-relevant processes, motivation, and the surrounding social environment, thereby extending explanations of creativity beyond one's personality and cognitive ability alone (Amabile, 1983, 2013). This proposition helped move the trajectory of creativity research away from perceiving creative potential as a fixed phenomenon by introducing influences such as motivation, task, knowledge and support. Innovation is not a concept about ideas alone, it includes the introduction and application of those ideas, meaning that a solution becomes innovation through testing and adoption at workplace. Therefore, creativity can be understood as a central input into innovation, but innovation is a more complete process that includes the movement of ideas from generation to application (Anderson et al., 2014; Amabile & Pratt, 2016).

Innovation capability adds a consistency layer on top of innovation which distinguishes isolated innovation outcomes from the capacity to repeatedly produce innovation-related activity. Innovation capability is well established at organisational level, while its conceptualisation at the individual level is less developed. This study therefore proposes IIC as a work-contextual individual capacity rather than as a personality label and includes both creative (idea generation) and non-creative elements (investigation, idea championing, planning, collaboration).

2.2 From Organisational Innovation Capability to Individual Innovation Capability

The concept of innovation capability has traditionally been analysed from the organisational level (Acosta-Prado, Romero Severiche Tafur-Mendoza, 2021). However, underlying organisational tools and mechanisms like management information systems (MIS), and knowledge management systems (KMS) do not independently produce innovation. Success of these systems depend partly on employees' ability to recognise opportunities, and to develop and implement ideas in daily work. This micro foundational view is important for innovation capability literature as organisational-level and individual-level studies are rarely bridged and

the crucial connection is not always clarified. This bridge can be understood as a process of analytical zooming where a broader entity, organisational innovation capability (OIC) with its technology, leadership structures, learning climate, and culture, may end up affecting whether and how employees are empowered in terms of opportunities, motivation, knowledge, and support needed to innovate. However, such organisational conditions still do not determine innovative behaviour; employees are expected to deploy the resources to respond to innovation-related demand (Hammond et al., 2011; Anderson et al., 2014; Lukes & Stephan, 2017). In this sense, the proposed IIC construct is treated as a micro-level capability connecting organisational context with enacted IWB.

The distinction also prevents IIC from being reduced to personality, because the literature consistently shows that factors like leadership, work design, climate, autonomy, knowledge sharing, support, and resources influence employees' innovative behaviour (Oldham & Cummings, 1996; Janssen, 2000; Hammond et al., 2011). Recent research on digital and AI-enabled innovation makes this bridge even more important as studies on digital innovation capability, AI-powered service innovation capability, and AI-supported knowledge management show that technological resources create innovation only when combined with human skills, managerial support, organisational learning, knowledge-sharing routines, and employees' willingness to use technology for innovation-related work (Kroh et al., 2024; Karkoulian & Boulos, 2025; Zhou et al., 2026).

2.3 Individual Innovation Capability, Individual Innovativeness, and Innovative Work Behaviour

Individual innovativeness describes a person's tendency towards novelty and early adoption, but is different from the proposed capability to innovate at work which may require the organisational knowledge and understanding, confidence or implementation skills to turn ideas into innovations.

The closest neighbouring construct is innovative work behaviour (IWB). IWB refers to intentional employee behaviour directed toward the creation, introduction, promotion, and application of new ideas within a work role, group, or organization (Janssen, 2000). Classic studies also describe such behaviour through lenses of terms like individual innovative behaviour or individual innovation proposing stages like idea generation, promotion, and realization (Scott & Bruce, 1994; Kleysen & Street, 2001). Later measurement models increasingly adopted the term IWB as the prevailing label and added more dimensions such as opportunity exploration, idea championing, implementation, search, communication, cooperation, overcoming barriers, and idea sustainability (Janssen, 2000; de Jong & den Hartog, 2010; Lukes & Stephan, 2017; Lambriex-Schmitz et al., 2020).

IWB describes innovation-related behaviour enacted by employees, whereas IIC is proposed as the underlying capacity to organise and deploy relevant resources in response to innovation-related demands. The distinction therefore consists of

distinguishing capacity from enactment, not from different innovation activities. Although IWB literature conceptualises it as a multidimensional construct, empirical evaluations do not consistently support the statistical separation of its proposed stages. Kleysen and Street (2001), De Jong and Den Hartog (2010), Salessi (2021), and Al-Khaldi and Bachkirov (2025) report rather varying degrees of overlap in terms of the dimensions used. Accordingly, the dimensional structure of the proposed IIC construct still represents an empirical question, not an assumption of the ready-to-applied framework.

3 METHODOLOGY

3.1 Literature Review Approach

The study adopts an integrative literature review approach to synthesise conceptual, empirical, and meta-analytical articles to inform construct boundary clarification and identification of candidate capability domains for the proposed IIC framework. The review included componential and dynamic creativity models, person-context creativity studies, and state-of-the-science reviews of creativity and innovation in organisations as conceptual background for the terms creativity, innovation, and capability (Amabile, 1983, 2013; Woodman, Sawyer, & Griffin, 1993; Oldham & Cummings, 1996; Shalley, Zhou, & Oldham, 2004; Anderson et al., 2014; Amabile & Pratt, 2016). Another group of articles included classic models and measurement studies such as Scott and Bruce (1994), Janssen (2000), Kleysen and Street (2001), De Jong and Den Hartog (2010), and Lukes and Stephan (2017) which defined and measured the behavioural stages of individual innovation. The review also included meta-analytic and review-based contributions, including Hammond et al. (2011) and Parveen & Reddy (2024), which synthesise predictors of individual-level innovation. The third group of studies was made up of recent scale-development, validation, and context-specific studies that aimed at assessing how IWB measurement has been adopted across different sectors like education, IT support, hospitality, and even across different cultures such as at Arabic, Indonesian, Indian, and GCC-dominant workplaces (Lambriex-Schmitz et al., 2020; Salessi, 2021; Dahiya & Raghuvanshi, 2022; Gkontelos, Vaiopoulou, & Stamovlasis, 2022; Ayoub, Almahamid, & Al Salah, 2023; Parnitvitidkun, Ponchaitiwat, Chancharat, & Thoumrungroje, 2024; Al-Khaldi & Bachkirov, 2025; Dahiya, 2025; Etikariena et al., 2025). The last group consisted of studies on myriad of contextual factors like leadership, fairness, psychological empowerment, learning climate, knowledge sharing, innovation-supportive climate, agile HRM, enterprise social media, digital competence, knowledge management, AI, digital innovation capability, and AI-powered service innovation capability (Janssen, 2000; Tierney & Farmer, 2002; Huang & Li, 2021; Jönsson, Unterrainer, & Kähler, 2022; Abhari, Zarei, Parsons, & Estell, 2023; Huu, 2023; Kroh et al., 2024; Herlina, Budiansyah, Janah, & Adryana, 2024; Coetzee & Leach, 2025; Karkoulou & Boulos, 2025; Altaf,

Tariq, Waqas, Alvi, & Lyu, 2026; Elsaied, 2026; Shamaileh, Mohammad, Aityassine, Aladwan, & Vasudevan, 2026; Zhou et al., 2026).

Empirical and scale-development sources were used to identify candidate domains. Foundational conceptual sources, in turn, were used and retained purposively for construct-boundary clarification and tracking the development pathway of the major innovation model even when they fell outside the scope of the Scopus-derived empirical sample.

The database search was conducted in Scopus on 26 June, 2026 using eight predefined TITLE-ABS-KEY search strings covering creativity and innovation, innovation capability measurement, organisational–individual innovation relationships, employee and individual innovation, individual innovation capability and innovativeness, IWB measurement, IWB process stages, and individual-level innovation measurement. All searches were restricted to publications from 2020 to 2026 (PUBYEAR > 2019 AND PUBYEAR < 2027). For each search, results were sorted using the Scopus relevance ranking and the 50 highest-ranked records were exported, producing 400 raw articles. Records were deduplicated using DOI and title matching, leaving 374 unique records. The complete search strings are reported in Supplementary Table S1.

The unique records underwent relevance screening based on their direct contribution to the study’s conceptual scope including individual-level innovation, IWB dimensionality and measurement, innovation capability, scale development and validation, and personal, organisational, or technological conditions relevant to employee innovation. An intermediate shortlist of 75 records was produced, which was later reduced to 29 records based on the raw relevance score. All the articles with scores 10 or below were excluded from the shortlist. One additional recent study identified outside Scopus, Abun and Macaspac (2023), was purposively included because of its direct relevance to the conceptual framework. Other 14 articles included were legacy pre-2020 studies which provided foundational conceptual basis for these more modern models to allow for adequate tracing of the conceptual evolution of IIC. Then all 44 articles were coded by the author into a complete 25-attribute matrix which covered bibliographic characteristics, study design and level of analysis, construct definition and role, theoretical basis, dimensional structure, measurement strategy, sample and data collection, analytical methods, reliability and validity evidence, main findings, limitations, and relevance to framework development. Codebook for the attributes is provided in Supplementary Table S2, whereas the full study-level extraction matrix is provided in Supplementary Table S3. Because coding was done solely by a single author, coded entries were rechecked against the source studies during synthesis as opposed to employing interrater agreement.

3.2 Framework Development Approach

The framework was developed to synthesise fragmented literature varying in design, context, constructs, measures, and outcomes into an integrated conceptual architecture for informing subsequent IIC measurement development and validation. The framework development followed four steps aimed at generating the conceptual synthesis: construct boundary clarification, dimension mapping, conceptual positioning, relationship mapping. At the first step, terms such as creativity, OIC, individual innovativeness, IWB, and IIC were clarified to establish the conceptual boundaries of the proposed construct. Second stage was informed through the literature review and mapped domains across existing IWB and individual innovation models, logging both repeated as well as less consistently represented domains across studies such as opportunity exploration, idea generation, promotion/championing, implementation/application, realisation, investigation/refinement and idea sustainability/embedding (Kleysen & Street, 2001; Lukes & Stephan, 2017; Lambriex-Schmitz et al., 2020; Dahiya & Raghuvanshi, 2022; Parnitvitidkun et al., 2024; Dahiya, 2025). Third stage of the study placed capability into a conceptual continuum in between its antecedents, also called psychological drivers or resources, such as creative self-efficacy, motivation, psychological empowerment, and psychological capital, and its behavioural output, IWB, which serves to compare the behavioural outcomes for employees with similar personal resources. The last stage of framework development incorporated organisational conditions like autonomy, job complexity, fairness, leadership support, learning climate, risk tolerance, and knowledge sharing and technological conditions such as access to digital and AI tools, enterprise social-media functionality, information accessibility, AI-enabled knowledge-management support, technological integration, reliability, and training; and organisational conditions such as digital innovation capability, and AI-powered service innovation capability as enabling or constraining factors. This step positioned contextual organisational and technological conditions as proposed developmental and activation influences whose relationships with personal resources, IIC, and IWB can be tested in future empirical research. Accordingly, recurrence of innovation related domains across the reviewed studies was treated as evidence for their inclusion as candidate capability domains, rather than as evidence of factorial distinctiveness or empirical validity.

4 LITERATURE REVIEW AND MEASUREMENT LIMITATIONS

4.1 Individual Innovation and IWB Models

Literature on individual innovation at workplace has historically evolved from early creativity models which identified condition that enabled individuals create new ideas of value. Amabile's componential model suggested four predictor variables domain relevant skills, creativity-relevant processes, task motivation,

and the social environment to explain creative performance (Amabile, 1983, 2013). Woodman et al. (1993) expanded on this logic by imagining creativity within an organization as an interplay of individual, group, and organisational factors. Oldham and Cummings (1996) later showed that not every job was capable of producing creative performance from its employees and that the best organisational contexts for it would be jobs with high complexity and supportive staff. They used multiple creativity indicators, including supervisor rated creativity, patents, and suggestion-programme outputs. Tierney and Farmer's (2002) research centered around creative self-efficacy as a main predictor of creative performance, while Shalley et al. (2004) synthesised different sources to demonstrate that creativity depends on both personal and contextual characteristics. Although an important part of broader organisational creativity and innovation literature, the concept of creativity does not directly concern real-life application of ideas, and thus, these models lacked explanatory power needed to explain innovation at work (Anderson et al., 2014). Amabile and Pratt's (2016) dynamic componential model attempts to create a multidimensional path from creative idea development toward innovation outcomes using motivation, affect, meaningful work, progress, and the work environment as factor variables thereby connecting the notions of individual creativity with organisational innovation.

IWB research is yet another tradition within the individual innovation literature dates back to Scott and Bruce's (1994) model which treated individual innovative behaviour as a process affected by the factors such as leadership, work-group relations, problem-solving style, and climate for innovation. This model also introduced one of the earliest measurement scales assessing innovation in three dimensions: idea generation, idea promotion, and idea implementation. Janssen (2000) introduced what is now known as IWB with its nine-item IWB scale including three items, each for idea generation, idea promotion, and idea realization. Its relative simplicity led to the wider adoption of this framework, however, many studies treated this three-dimensional score as one due to their intercorrelated nature (Janssen, 2000; Salessi, 2021; Al-Khaldi & Bachkirov, 2025). Kleysen and Street (2001) expanded upon this model to include opportunity exploration, generativity, formative investigation, championing, and application, while De Jong and Den Hartog (2010) refined it to include idea exploration, idea generation, idea championing, and idea implementation. The former five-factor model had weak fit, whereas the latter four-dimensional IWB scale fit better than alternative models with dimensions still highly correlated. Lukes and Stephan (2017) separated employee innovative behaviour from innovation outcomes by developing the Innovative Behaviour Inventory and Innovation Support Inventory, with six stage model which included idea generation, idea search, idea communication, idea implementation starting activities, involving others, and overcoming obstacles. Lambriex-Schmitz et al. (2020) validated a 44-item multidimensional IWB for vocational teachers using Rasch analysis and CFA. It added idea sustainability domain, which was split into external dissemination and internal embedding, while idea realization was broken down to criterion-based implementation and learning-based communication, respectively. Salessi (2021)

ran Janssen's IWB scale on an Argentinian sample and found it was best represented as a unidimensional measure. Gkontelos, Vaiopoulou, and Stamovlasis (2022) further validated the model for Greek teachers and found support for factors such as idea generation, idea promotion, idea realisation, and idea sustainability, but not opportunity exploration. Ayoub, Almahamid, and Al Salah (2023) also validated a five-factor higher-education model but in the GCC context, keeping opportunity exploration, idea generation, idea promotion, idea realisation, and idea sustainability. Al-Khaldi and Bachkirov (2025) also validated an Arabic version of De Jong and Den Hartog's IWB scale concluding the poor fit for idea exploration, ending up in an eight-item unidimensional Arabic IWB scale.

IWB literature has also examined contextual conditions affecting innovation, including organisational climate, organisational trust, and perceived organisational support (Battistelli, Odoardi, Cangialosi, Di Napoli, & Piccione, 2022; Utomo et al., 2023). Individual and attitudinal conditions have also been examined, including job satisfaction and personality in relation to IWB (Mustafa, Coetzer, Ramos, & Fuhrer, 2021). While Janssen's (2000) analysis focused on employees' perceptions on effort–reward fairness, Hammond et al.'s (2011) meta-analysis confirmed the great role of individual differences, motivation, and job characteristics which specifically affected idea implementation. Huang and Li (2021) looked into small software firms and found that innovation climate affects employee's knowledge acquisition, dissemination, and responsiveness to knowledge while Phil-Thingvad and Klausen's (2021) research on public service organisation employees' found how the dimensions like idea generation, promotion, and realisation were influenced by the organisational conditions such as knowledge of innovation strategy, risk-tolerant culture, and autonomy. Jønsson, Unterrainer, and Kähler (2022) added that job autonomy and trust may support innovation through distributed leadership agency, whereas Herlina et al. (2024), Altaf et al. (2026), and Elsaied (2026) demonstrated the great role of other leadership styles such as transformational, servant, and virtuous leadership styles, respectively, on IWB through cognitive drivers like knowledge sharing, psychological empowerment, engagement, and moral identity.

Some studies showed sensitivity of IWB framework to matters like culture, sector, and technology adoption mindset. Nguyen, Ngo, and Gregory (2022) used individual innovation capability as a moderator of online knowledge sharing but measured it as a short unidimensional construct. Dahiya and Raghuvanshi (2022) validated a five-factor IWB model for Indian apparel manufacturing, which included opportunity exploration, idea generation, information investigation, idea championing, and idea implementation/application and later, Dahiya (2025) applied it for green IWB in Indian hospitality, Parnitvitidkun et al. (2024) employed an eight-dimensional IWB model for IT helpdesk support staff, including opportunity exploration, idea sharing, idea generation, idea implementation, idea organisation, idea learning, idea promotion, and idea realisation. Etikariena et al. (2025) developed an Indonesian intention-for-IWB scale favouring intention-based framework versus past behaviour-based one to

improve predictive power. Huu (2023), Abhari et al. (2023), Karkouliau and Boulos (2025) showed the role of digital competence, enterprise social media, knowledge management, AI use, respectively. Kroh et al. (2024) measured organisational digital innovation capability using seven dimensions, and Zhou et al. (2026) developed a higher-order AI-powered service innovation capability scale that included three dimensions.

Table 1 compares the proposed IIC framework with creativity, individual innovativeness, IWB, and organisational innovation capability models.

Table 1 – Comparison of IIC with neighbouring individual-innovation constructs

Construct/model	Typical dimensions	Key distinction from proposed IIC
Creativity	domain knowledge, creative processes, motivation, idea generation	Primarily concerns ideation rather than capacity across the full innovation process
Individual innovativeness	willingness to adopt, novelty orientation	Orientation towards innovation rather than capacity to perform innovation-process functions
Kleysen & Street (2001)	opportunity exploration, generativity, formative investigation, championing, application	Provides several process domains incorporated into the proposed architecture, but treats them behaviourally
de Jong & den Hartog (2010)	idea exploration, generation, championing, implementation	Measures what employees report doing rather than separating underlying capability from enactment
Lukes & Stephan (2017)	idea generation, search, communication, implementation, involving others, overcoming obstacles	Explicitly separates behaviour from support, but not latent capability from actual behaviour
Lambriex-Schmitz et al. (2020)	exploration, generation, promotion, realisation, sustainability	Introduces sustainability but retains a behavioural measurement referent
Organisational innovation capability	routines, resources, technologies, processes	Organisational rather than individual level of analysis

4.2 Research Gaps and Contribution

The reviewed literature provides a strong foundation for understanding, measuring and conceptualising creativity, IWB, and the conditions that support employee innovation. However, the existing studies have not sufficiently specified IIC as a distinct concept or established a conceptual architecture from which a systematic measurement model can be developed. The creativity models explain how individuals produce novel and useful ideas, while the behaviour models fills in the gap of capturing what employees actually do, such as generating, promoting, and implementing ideas (Amabile, 1983, 2013; Oldham & Cummings, 1996; Amabile & Pratt, 2016; Scott & Bruce, 1994; Janssen, 2000; de Jong & den Hartog, 2010). OIC models explain firm-level resources and routines, but they often do not

specify the employee-level capability through which innovation is realised (Kroh et al., 2024; Zhou et al., 2026). That being said, individual innovation capability, a concept focusing on predicting whether employees have the underlying capability to innovate as opportunities present themselves, has essentially remained positioned between creativity, innovativeness, IWB, and OIC without being sufficiently developed as its own construct. A direct consequence of this for organisations might be the risk of omitting the capable employees who either failed to demonstrate their abilities in lieu of psychological and organisational conditions in favour of those who had the right opportunities and performed accordingly. The proposed framework therefore introduces unequal opportunity as a testable explanation for the difference between the observed IWB and underlying capability. Proposed contribution is thus about separating opportunity and contextual conditions explicitly from capability and its behavioural enactment.

The second gap is dimensional. Existing studies disagree on the structure of individual innovation-related behaviour. Some models propose three stages, others four, five, six, seven, or eight dimensions, including the dimensions such as idea generation, idea promotion, idea realization, opportunity exploration, formative investigation, idea championing, idea implementation, idea search, involving others, overcoming obstacles, idea learning, and idea sustainability (Janssen, 2000; Kleysen & Street, 2001; de Jong & den Hartog, 2010; Lukes & Stephan, 2017; Lambriex-Schmitz et al., 2020; Parnitvitidkun et al., 2024). Additionally, the empirical results of some studies support multidimensional models, while others find that dimensions collapse into one broader factor (Dahiya & Raghuvanshi, 2022; Ayoub et al., 2023; Parnitvitidkun et al., 2024; Dahiya, 2025; de Jong & den Hartog, 2010; Salessi, 2021). For instance, De Jong and Den Hartog (2010) found strong correlations among dimensions and Salessi (2021) supported a unidimensional Janssen scale; while Dahiya and Raghuvanshi (2022), Ayoub et al. (2023), Parnitvitidkun et al. (2024), and Dahiya (2025) supported multidimensional structures. This inconsistency suggests that the field lacks agreement on whether individual innovation should be measured as a single construct, a set of stages, or a higher-order capability, and therefore, while creating a new framework it is crucial to enable its theoretical multidimensionality as well as making sure that it is empirically testable as a possible higher-order construct.

The third gap involves the fact that many scale development and measurement models do treat cognitive and psychological drivers as external antecedents, not a contextually ingrained part of individual innovation. However, literature supports that individual innovation is shaped, not simply affected by leadership, autonomy, fairness, psychological empowerment, creative self-efficacy, knowledge sharing, organisational climate, learning climate, and risk tolerance (Tierney & Farmer, 2002; Hammond et al., 2011; Huang & Li, 2021; Jönsson et al., 2022; Herlina et al., 2024; Coetzee & Leach, 2025; Altaf et al., 2026; Elsaied, 2026). Therefore, integrating them into a capability perspective could help bridging the

gap between the measurement of behaviour and the conditions that make such behaviour possible.

The fourth gap concerns how existing individual-level IWB scales designed before AI-enabled and digitally mediated work became central to innovation do not consider whether current measures can sufficiently capture innovation capability in modern workplaces. Digital competence, enterprise social media, knowledge management systems, AI tools, and AI-powered service innovation capability increasingly shape how employees access information, collaborate, generate ideas, and implement solutions (Huu, 2023; Abhari et al., 2023; Karkouliau & Boulos, 2025; Zhou et al., 2026). Even though the rate of change does not automatically render older scales obsolete, as evidenced by many recent studies that still rely on the older frameworks of measurement, it suggests that the existing frameworks are incomplete at the very least and need refinement.

Taken together, the reviewed literature provides extensive measures of enacted innovative behaviour but does not isolate the individual-level capacity underlying such behaviour from its personal-resource antecedents and contextual opportunities. This provides basis for proposing IIC as a distinct conceptual architecture for future measurement development.

5 PROPOSED MULTIDIMENSIONAL FRAMEWORK

Referring to the discussion of conceptual terms and review of research gaps performed previously, the present study proposes a multidimensional conceptual framework of IIC for future measurement development and empirical validation. It has four main components: personal innovation resources, IIC, organisational and technological development and activation conditions, and IWB, followed by innovation outputs and or workplace impact. The first conceptual component concerns personal innovation resources, which are the internal individual-level drivers that provide foundation from which IIC develop. The second component is a construct that represents individual's latent capability, IIC, which builds on six dimensions that consists of classic IWB stages together with some dimensions that appeared in literature revision but were not systematically tested: opportunity exploration, idea generation, idea development, idea mobilisation, idea realisation, and idea sustainment. Third component, IWB, represents observable enactment of the same stages of innovation. Thus, while IIC measures the capacity of a person to engage in those six dimensions, IWB is concerned with the question whether the measured capability across those actions was actually enacted in specific period and if yes, also the level of intensity by which it was performed. Fourth component represents the contextual conditions, manifested in organisational and technological factors that enable, or constrain the capability development as well as the activation of the dimensions attributes allowing for the conversion of capability into behaviour across the given dimensions.

5.1 Core Dimensions of Individual Innovation Capability

The proposed framework conceptualises individual innovation capability as a multidimensional construct consisting of six core dimensions: opportunity exploration, idea generation, idea development, idea mobilisation, idea realisation, and idea sustainment with some of the later stages defined in two facets. These dimensions and their facets taken together synthesise the main stages identified across classic and recent IWB models: opportunity exploration is defined as the capability to recognise problems, search for opportunities, notice emerging needs, and identify areas where improvement is possible; idea generation refers to the capability to produce novel ideas, solutions, procedures, or approaches of value; idea development is the capability to search for information, assess feasibility, evaluate advantages and disadvantages, learn from feedback, and improve ideas before implementation; idea mobilisation referring to the social capability to communicate ideas, gain support, persuade colleagues or managers, build coalitions, and mobilise resources; idea realisation is the capability to transform ideas into practice, develop plans, test solutions, apply changes, and integrate new practices into daily work; idea sustainment implies the capability to maintain, disseminate, institutionalise, and improve innovations over time.

The framework separates idea development, mobilisation, realisation and sustainment into two facets of their own. Idea investigation and validation is the first step in the process of idea development and serves as the first serious attempt at exploring the idea through research and other people's and even literature's perspectives. Following the investigation and validation, idea refinement and elaboration facets render the idea ready for its immediate mobilisation by designing a clear step-by-step plan that specifies how the idea would work in practice and then revise it based on the evidence and feedback while also identifying potential risks and threats. After the idea is sufficiently developed, idea mobilisation domain begins with promotion and communication through which an employee presents the idea in front of the test audience, usually their colleagues, to incite feedback and preapproval. Championing and resource mobilisation facet of mobilisation goes beyond communication by building active support for the idea, securing funds and material resources needed for idea realisation. Realisation is simply made up of initiation of implementation – using acquired resources in preparation for application – and operational application of the idea. The final stage, idea sustainment, involves idea continuation and adaptation, which allows the idea to be continually applied through changing circumstances, sealed by idea embedding and diffusion which helps idea to engender multiple uses across multiple industrial and cultural uses. Idea sustainment is distinguished from an innovation outcome because it concerns the capacity to maintain, adapt, embed and diffuse an innovation after initial implementation. Actual continuation or diffusion constitutes enacted behaviour, whereas resulting improvements in performance, quality, products or services constitute downstream outcomes.

Table 2 provides a summary for the inclusion and exclusion boundaries used for distinguishing the six candidate IIC domains.

Table 2 – Conceptual boundaries of the candidate IIC domains

Candidate domain	Includes	Excludes
Opportunity exploration	detecting problems, unmet needs and improvement opportunities	evaluating or modifying an already identified idea
Idea generation	producing novel and potentially useful alternatives	evaluating feasibility or selecting among developed alternatives
Idea development	investigation, validation, feasibility assessment, refinement and elaboration	generating the initial idea; securing stakeholder support
Idea mobilisation	communicating, championing, building coalitions and securing resources	physically implementing or applying the idea
Idea realisation	implementation initiation, testing and operational application	maintaining an already implemented innovation over time

5.2 Differences between the Components of the IIC Framework

Personal innovation resources describe what employees possess, IIC describes what they can integrate and deploy, IWB describes what they actually do under specific workplace conditions, and contextual conditions point to the factors that may influence employee's ability to develop capability and/or convert it to IWB. This distinction introduces the assumption of inequality of opportunity into the explanation of individual innovation because observation of lower IWB scores could be due to the reasons other than for low innovation capability like the lack of autonomy, time, information, support, or technological access. Innovation opportunity exposure is treated separately from both IIC and contextual support. It refers to the extent to which an employee encounters or is given access to situations in which innovation-related capacity can be enacted, such as identifiable improvement problems, permission to propose changes, access to relevant stakeholders, participation in implementation, and sufficient task responsibility. Future empirical studies should measure such exposure independently during the same time period as IWB so that low behavioural enactment can be distinguished from lack of opportunity to act. The framework therefore proposes that similar personal resources can produce different behavioural outcomes and why low observed IWB cannot automatically be interpreted as low innovation capability.

Under the framework, personal innovational resources include domain knowledge, creativity-relevant thinking skills, motivation, self-efficacy, empowerment, psychological capital, openness, and digital competence. However, the attributes such as autonomy, psychological safety, leadership support, access to time and knowledge, and fair recognition are treated as organisational development and activation conditions even though some of them might seem like internal resources. Technological development and activation conditions include the usability, integration, reliability, explainability, associated training, privacy implications, and potential to encourage overreliance of digital and AI tools.

Together, the interaction of these components leads to the innovation outputs or workplace impacts (Figure 1).

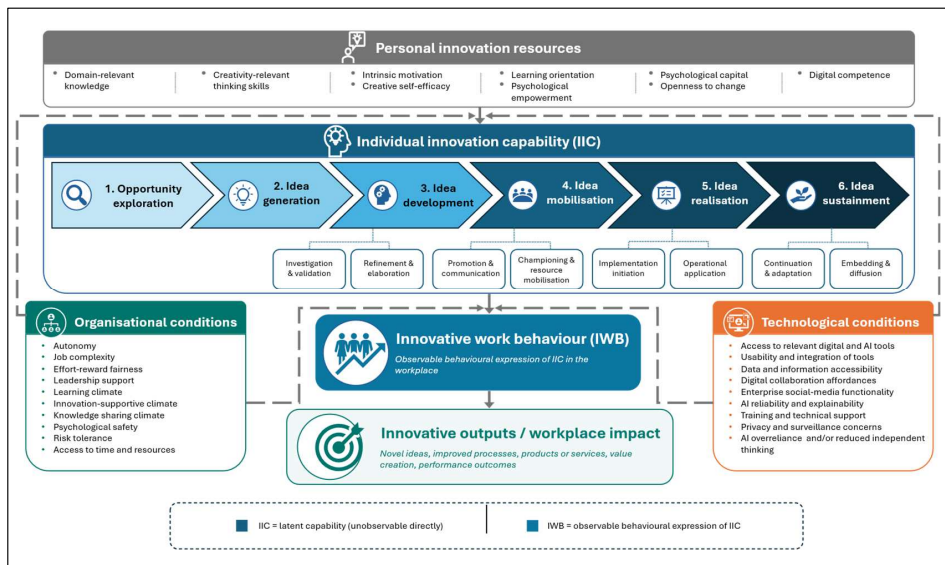


Figure 1 – Detailed framework of individual innovation capability

5.3 Conceptual Propositions

Because the present article develops a conceptual framework rather than testing primary empirical data, it is expressed through propositions that translate the reviewed literature into a coherent model of IIC as opposed to statistical hypotheses.

Proposition 1: Six candidate capability domains represent distinguishable but related components of IIC: opportunity exploration, idea generation, idea development, idea mobilisation, idea realisation, and idea sustainment.

The basis for conceptualising individual innovation capability as a multidimensional process capability expressed through these dimensions is rooted in how classic IWB models identify idea generation, promotion, and realisation as central behavioural stages, combined with later models adding opportunity exploration, championing, implementation, information investigation, idea search, overcoming obstacles, and sustainability.

Proposition 2: Personal innovation resources positively contribute to the development of individual innovation capability.

Personal innovation resources such as creativity-relevant skills, intrinsic motivation, creative self-efficacy, psychological empowerment, and psychological capital form the technical and psychological base of individual innovation capability, supporting employees' ability to engage in innovation-related work. This proposition is supported both by the earlier research and studies such as

componential theory, findings on creative self-efficacy, as well as by more recent studies which established that psychological empowerment mediates the relationship between servant leadership and IWB.

Proposition 3: Supportive organisational and technological development conditions positively contribute to the development of IIC.

Personal innovation resources do not automatically translate into innovation capability; their development depends on how workplace conditions enable or constraint their deployment.

Proposition 4: Innovation opportunity exposure constitutes a boundary condition for the behavioural enactment of IIC.

The importance of this proposition is displayed through the role of the access to opportunities in influencing the innovation outputs. Employees with better access to innovation-related tasks, stakeholders, decision-making and implementation activities will perform higher than the same employees with similar levels of IIC who lack the access to the same opportunities.

Proposition 5: IIC positively predicts subsequent IWB when employees are exposed to relevant opportunities for innovation.

IWB is the observable expression of individual innovation capability, which is consistent with literature-based definitions, but it also extends them by positioning behaviour as the outcome of a broader capability. This proposition suggests that employees who can recognise opportunities, generate ideas, develop them, mobilise them, realise them, and sustain them are more likely to display innovative behaviours in their work roles.

Proposition 6: Supportive organisational and technological activation conditions strengthen the relationship between IIC and IWB, while IWB is expected to contribute positively to subsequent innovation outputs and workplace impact.

The same level of individual innovation capability may produce different levels of observed IWB depending on contextual conditions. Capability may remain unrealised when employees lack autonomy, support, resources, psychological safety, or technological access, whereas supportive leadership, learning climate, innovation-supportive culture, knowledge-sharing routines, and effective digital tools may facilitate its conversion into behaviour.

Together, these propositions define individual innovation capability as a multidimensional, person-context construct clarifying the theoretical sequence of the model through four conceptual components: personal innovation drivers contributing to capability; organisational and technological activation conditions shaping its development and expression; and IWB representing its observable outcome.

6 DISCUSSION

6.1 Theoretical Implications

Comparison with established IWB models reveals both continuity and a substantive conceptual departure. Classic IWB models like Janssen (2000), de Jong and den Hartog (2010) treat idea generation, promotion, and realisation as behaviours whereas the proposed framework strategically relocates them and adds opportunity exploration, idea development, idea mobilisation, and idea sustainment to the capability level. Opportunity exploration dimension appears in Kleysen and Street (2001), De Jong and Den Hartog (2010) idea exploration, and later multidimensional instruments applied for education, manufacturing, IT, and green hospitality (Lambriex-Schmitz et al., 2020; Dahiya & Raghuvanshi, 2022; Parnitvitidkun et al., 2024; Dahiya, 2025). Although some validation studies failed to establish exploration as a separate empirical factor (Gkontelos et al., 2022; Al-Khaldi & Bachkirov, 2025), it remains conceptually important and incorporated into the model. Idea generation is central to creativity theory, as it provides for the strongest bridge between creativity and innovation, appearing consistently in IWB models (Amabile, 1983; Janssen, 2000; de Jong & den Hartog, 2010; Anderson et al., 2014). Idea development activity is strongly visible in Kleysen and Street's (2001) formative investigation and in Dahiya and Raghuvanshi's (2022) and Dahiya's (2025) information investigation dimension, as well as many studies on knowledge management, learning climate, and digital competence, which indirectly support the inclusion of this dimension to the framework, as evidenced by the employees' need for access to knowledge and learning processes to convert ideas into workable innovations (Huang & Li, 2021; Huu, 2023; Karkoulouli & Boulos, 2025). Idea mobilisation stage appears in early literature such as Scott and Bruce (1994), Janssen (2000), and even in De Jong and Den Hartog (2010), and Lukes and Stephan (2017) and is important as it recognises the role of social approval, and collaboration for making workplace innovation happen. Idea realisation dimension appears across nearly all IWB models (Janssen, 2000; Kleysen & Street, 2001; de Jong & den Hartog, 2010; Dahiya & Raghuvanshi, 2022). Conversely, idea sustainment is a rather new step that is increasingly gaining traction with the recent IWB literature. Lambriex-Schmitz et al. (2020) added idea sustainability to educational IWB by distinguishing external dissemination and internal embedding. Gkontelos et al. (2022) and Ayoub et al. (2023) also supported sustainability-oriented IWB dimensions. These elements have appeared separately in multidimensional models but have rarely been assembled into one capability architecture (Kleysen & Street, 2001; Lambriex-Schmitz et al., 2020; Parnitvitidkun et al., 2024).

Apart from separating its IWB and IIC components, the framework also differentiates between personal innovation resources and capability components. This separation is important in terms of resolving an ambiguity that remains within much of the existing literature which mostly treats the capability the same as resources. The literature identifies several recurring personal innovation resources,

including creativity-relevant skills, intrinsic motivation, creative self-efficacy, psychological empowerment, psychological capital, knowledge resources, and openness toward change. Amabile's (1983, 2013) approach suggests that such drivers include domain-relevant skills, creativity-relevant processes, and task motivation; Oldham and Cummings (1996) specify that job complexity, supportive management, supervision that allows for autonomy are important factors for innovation at workplace; Tierney and Farmer (2002) add creative self-efficacy to the list of the creative performance predictors. This is supported by later studies showing that creative self-efficacy is linked to innovation intention and behaviour (Shamaileh et al., 2026), and that psychological empowerment mediates the relationship between servant leadership and IWB (Altaf et al., 2026). Another pillar of personal innovation resources is psychological capital, as employees with higher hope, efficacy, resilience, and optimism are shown to pursue innovation despite barriers (Altaf et al., 2026). These findings suggest that individual innovation capability requires more than technical knowledge but also employees' confidence, motivation and other cognitive resources when it comes to producing useful new ideas, engaging in non-routine work, and acting under uncertainty. However, many of these studies have treated these factors as contextual influences or antecedents to IWB, and in some cases as proxies for the capability to perform innovative work. Accordingly, the proposed framework treats personal innovation resources as antecedent factors of capability itself, not the enacted behaviour because one still needs to translate these resources into capability well before converting the latter to the behaviour.

The framework adopts person-context interpretation of capability, treating its fourth component – organisational and technological enabling/constraining conditions – as independent variables influencing IIC. This preserves the individual nature of the construct while also acknowledging the external factors that affect its development and conversion into behaviour. This is consistent with Scott and Bruce's (1994) finding that leadership, workgroup relations, and climate shape individual innovative behaviour, and with Hammond et al.'s (2011) metaanalysis showing that motivation, job characteristics, leadership, climate, resources, and support predict individual innovation. Organisational conditions include autonomy, job complexity, fairness, leadership support, learning climate, innovation-supportive climate, knowledge sharing, and risk tolerance as per literature (Oldham & Cummings, 1996; Janssen, 2000; Lambriex-Schmitz, Van Der Klink, Beausaert, & Segers, 2025; Coetzee & Leach, 2025). According to the series of leadership studies, transformational, servant, and virtuous leadership styles can be instrumental in supporting IWB through tacit knowledge sharing, psychological empowerment, work engagement, and moral identity (Herlina et al., 2024; Altaf et al., 2026; Elsaied, 2026). Technological conditions include factors such as digital competence, access to enterprise social media, knowledge management tools, which support innovative behaviour, ideation, collaboration, given that employees have the right training, willingness to engage and climate required to convert capability to observable innovative behaviour (Huu, 2023; Abhari et al., 2023; Karkouloulian & Boulos, 2025). Therefore, the main contribution

of the study is its separation of resources, deployable capability, enacted behaviour and the contextual development and activation conditions. Future validation should therefore test not only competing dimensional structures, but also whether IIC remains empirically distinct from personal resources and IWB, and whether activation conditions affect particular dimensions differently.

6.2 Practical Implications

If empirically validated, the framework could provide organisations with a new diagnostic structure for identifying why employee innovation does or does not occur. The reasons why an employee scores low on IWB could reflect more than general lack of innovativeness such as insufficient personal resources, weak capability in a particular innovation stage, restrictive organisational conditions, unsuitable technological systems, or simply limited opportunity to act, allowing the organisation to direct development resources towards the right problem. Personal resources can inform recruitment and development; future operationalisations of IIC may combine capability-oriented statements, scenarios, work samples, or multisource ratings; IWB should be measured as time-bounded enactment; and outputs should be evaluated separately through implemented improvements or workplace effects. This would reduce the risks of penalising capable employees whose opportunities were not equally enabling as with many others who eventually end up showing higher IWB outcomes.

In practice, assessment should therefore consider a more robust capability profile rather than a minimalist innovation score consisting of visible innovation outcomes alone. That could also help the organisation manage its human resources more efficiently as well as more effectively by separating the employees who are stronger in recognising opportunities and generating ideas from those more successful in investigating feasibility, mobilising support, or embedding improvements. Idea development weaknesses may require training in searching information, experimenting with different edge cases, evaluating the evidence, or integrating feedback more effectively. Weaknesses in mobilisation may require stakeholder analysis, persuasive communication, coalition building, and resource negotiation, whereas realisation and sustainment weaknesses may call for project management, implementation planning, monitoring, adaptation, and knowledge-transfer support. Applying this stage-specific diagnostics approach is consistent with the evidence from the literature that different forms of support may be more important at different points in the innovation process (Lambriex-Schmitz et al., 2020).

A staged validation is therefore required before practical diagnostic use. First, candidate items should be derived from the six domain definitions and interviews while explicitly referring to the capacity, addressing only one capability domain at a time and excluding the contextual conditions and innovation outcomes. Second, expert review should determine content relevance. Third, exploratory factor analysis (EFA) should be conducted on pilot data, followed by confirmatory factor

analysis (CFA) using an independent sample to compare one-factor, correlated six-factor, higher-order, and composite specifications. Fourth, reliability and convergent and discriminant validity should be tested against constructs like creative self-efficacy, individual innovativeness and IWB. Fifth, measurement invariance, longitudinal predictive validity and incremental validity should be examined across occupations, cultures and other demographic groups.

7 CONCLUSION

This article addresses conceptual fragmentation surrounding innovation at individual level by proposing a multidimensional conceptual architecture of IIC. While the existing research has provided strong foundations through creativity models, IWB scales, OIC perspectives, and studies of personal, organisational, and technological antecedents, these traditions have generally remained separated and did not distinguish between what employees can do and actually do which has been the main outcome of the IWB research. The capability residing at the individual level and connecting these streams has remained insufficiently specified.

The proposed framework distinguishes three sequential components of individual innovation – personal innovation resources, IIC, and IWB – and fourth cross-cutting component – contextual (organisational and technological) development and activation conditions. It defines personal innovation resources as employee's knowledge, skills, and psychological attributes which lay the foundation for innovation capability. IIC is conceptualised as individual's integrated capacity to organise and deploy those resources across six candidate capability domains: opportunity exploration, idea generation, idea development, idea mobilisation, idea realisation, and idea sustainment. IWB is defined as the actual enactment of this capacity during a specified period. Organisational and technological development and activation conditions operate as factors enabling or constraining the development of IIC, and its conversion to observable IWB, while innovation outputs and workplace impact are viewed as downstream outcomes of this process.

The framework therefore offers three principal contributions: it clarifies the conceptual boundaries among creativity, personal innovation resources, IIC, and IWB; it synthesises fragmented models into an integrated conceptual structure and proposes six candidate capability domains for future empirical validation; and it incorporates inequality of opportunity assumption across all sequential components of individual innovation. The proposed six-domain structure should therefore be interpreted as a conceptual architecture for future operationalisation, not as an empirically validated measurement model. The framework remains conceptual and provides a theoretical basis for future measurement development and empirical validation to determine whether IIC can become a theoretically distinct and practically useful construct for understanding how employees contribute to workplace innovation.

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ABOUT THE AUTHOR

Laman Gasimzade ORCID: 0009-0005-5149-3620 – MSc., doctoral researcher in Business and Management at the Hantos Elemér Doctoral School of Business, Management and Regional Sciences, Faculty of Economics, University of Miskolc, Miskolc, Hungary, e-mail: laman.gasimzada97@gmail.com.

CONFLICTS OF INTEREST

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Perceived Quality of AI-Supported Recruitment: The Role of Explainability, Trust and Human Control

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Coi Tran, Radoslav Delina

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ABSTRACT

Purpose: This paper examines perceived quality of Artificial Intelligence (AI)-supported recruitment by testing how explanation, confidence information, practical AI experience, trust, willingness to use AI, perceived fairness and human control shape evaluations of AI candidate-ranking recommendations.

Methodology/Approach: The study uses an anonymous survey of Human Resources (HR)-related respondents (N = 145) and a randomised scenario comparing AI ranking without explanation with ranking supported by brief reasoning and confidence information. We use reliability checks, regression models, mediation and automation tests.

Findings: Practical AI experience significantly moderated the effect of explanation on trust and showed a weaker pattern for willingness to use AI. The moderation was not significant for perceived fairness. Intention to use AI was associated with trust, perceived usefulness, human control and prior AI experience.

Research Limitation/Implication: The non-probabilistic sample has a strong Central European component. The results measure perceptions rather than behavioural outcomes or audited fairness.

Originality/Value of paper: The paper shows that explanation and confidence strengthen trust mainly among AI-experienced respondents but do not significantly improve perceived fairness. It distinguishes between trusting AI as decision support and being convinced that AI-supported ranking is fair to candidates.

Category: Research paper

Keywords: artificial intelligence; recruitment; perceived quality; explainability; human control

Research Areas: Management of Technology and Innovation; Quality by Innovation

1 INTRODUCTION

Artificial intelligence (AI) is increasingly applied in recruitment and candidate selection processes, from vacancy drafting, sourcing and candidate communication to screening, ranking and interview support. Existing studies show that AI can improve not only the speed or scalability of recruitment, but also they emphasise ethical risks related to opacity, algorithmic bias, privacy and accountability (Hunkenschroer & Luetge, 2022; Will, Krpan, & Lordan, 2023; Fabris et al., 2025). For Human Resources (HR) managers, the central question is therefore not only whether AI can accelerate recruitment processes, but whether AI-supported recruitment can be implemented as a high quality, trustworthy and fair decision-support process.

This paper focuses on AI-supported recruitment as a quality and innovation management problem rather than only an HR technology issue. In recruitment, quality goes beyond speed or cost reduction because it also concerns the reliability of recommendations, transparency, human control or auditability and fairness. In this study, we perceive AI quality as a socio-technical evaluation of AI decision support, whether HR professionals perceive the recommendation as useful, understandable, trustworthy, controllable and fair. Quality 4.0 and human-centred quality-management literature provide a useful basis for this impact because they connect data-driven decision support with people, processes, governance and total organisational value (Liu, Liu, Gu, & Yang, 2023; Carvalho, Dias, Dias, & Sampaio, 2024; Sony, Antony, & Douglas, 2020). Based on Quality 4.0 and human-centred quality-management thinking approaches, this paper positions AI-supported recruitment as a sensitive decision-support process where quality is not limited to automation and its performance. It also depends on whether HR professionals perceive AI recommendations as understandable, trustworthy and fair.

The empirical contribution of this study is based on a survey of HR-related professionals with a randomised scenario-based module. The study tries to reveal whether brief reasoning and confidence information attached to an AI-supported recruitment recommendation improves trust, willingness to use AI and perceived fairness, and whether practical AI experience changes these effects. The paper contributes to the literature by separating three outcomes that are often implicitly connected: trust in the AI output, readiness to use the AI tool and perceived fairness of the AI-driven recruitment. This distinction is practically important because an HR user may understand and validate AI recruitment recommendation and may trust the recommendation as useful decision support, while still not being convinced that the ranking is fair, non-discriminatory and valid across candidate groups.

2 LITERATURE SURVEY

Quality and innovation management are increasingly influenced by the use of artificial intelligence in decision-making processes across the whole organisation. Quality 4.0 is commonly described as the alignment of quality-management practices with digital technologies, advanced analytics and data-driven decision support, while a more human-centred quality perspective emphasises the role of people, governance and social impact of technological esp. AI-driven decisions (Sony et al., 2020; Liu et al., 2023). Recent literature also highlights that digital quality is not a purely technical agenda. It requires data governance, leadership, training, culture, process integration and human interaction in quality planning, assurance, control and improvement (Liu et al., 2023; Carvalho et al., 2024). This perspective is relevant for AI-supported recruitment because recruitment is not only an HR technology issue. It is a quality-sensitive service and decision-support process in which AI may improve speed, scalability and consistency, but may also introduce opacity, bias, insufficient human control and fairness concerns.

AI-enabled recruitment has been studied as both an opportunity and a risk. Reviews and conceptual frameworks show that AI can support several stages of the recruitment pipeline. These include vacancy generation, sourcing, screening, candidate matching, ranking, assessment as well as coordination (Hunkenschroer & Luetge, 2022; Chen, 2023; Will et al., 2023). The HIRE framework suggests that AI can be equal or superior to human recruiters in efficiency and some performance-related outcomes, but perceptions of AI hiring are often worse than perceptions of human hiring, especially in relation to trust and perceived humaneness (Will et al., 2023). At the same time, algorithmic hiring is considered as a sensitive organisational decision-support process where historical data and opaque modelling choices can reproduce or activate discrimination (Raghavan, Barocas, Kleinberg, & Levy, 2020; Fabris et al., 2025). Ethical reviews therefore recommend transparency, human oversight, auditing, data governance and organisational accountability as necessary conditions for responsible AI-enabled recruitment (Hunkenschroer & Kriebitz, 2023; Kazim, Koshiyama, Hilliard, & Polle, 2021).

A second stream of research focuses on explainability, trust and general adoption. In HR, stakeholders frequently ask how AI recommendation, final ranking, rejection or prioritisation a potential candidate depends on perceived usefulness, transparency, controllability and trust in line with recruiters' acceptance of AI recommendations (Laurim, Arpacı, Prommegger, & Krcmar, 2021; Lacroux & Martin-Lacroux, 2022). Studies of human-AI and augmented hiring processes also show an interesting pattern in which reactions are more favourable when AI supports rather than replaces human decision-makers (Gonzalez et al., 2022). However, explanations according mentioned studies shouldn't be treated as a universally accepted trust-building mechanism. In human-AI decision support, explanations may increase fairness perceptions and reliance, but they do not necessarily help users identify correct versus incorrect recommendations or detect systematic bias (Schoeffer, De-Arteaga, & Kuehl, 2022). From a quality-

management perspective, this means that explainability should be understood as one quality pillar of AI decision support, not only as sufficient evidence that the AI-supported recommendation is valid, reliable or fair.

The literature also suggests that fairness of AI is not identical to user trust as it includes procedural justice, non-discrimination, validity, explainability and other features that outcomes do not disadvantage protected or vulnerable groups (Hunkenschroer & Kriebitz, 2023; Fabris et al., 2025). Within an audit-oriented research, studies stress that fairness assurance requires bias measurement, model assessment and mainly transparency of decision rules and governance mechanisms going beyond individual user perceptions (Kazim et al., 2021). Recent research in personnel selection also suggests that explanations can improve applicant's fairness perceptions under some conditions (Malin, Fleiß, Ortlieb, & Thalmann, 2025). However, this does not resolve whether HR professionals, as organisational users of AI decision support, interpret the same explanation and confidence cues as signals of trust, use-readiness and fairness in the same way. This gap opens an important research space between applicant-side fairness perception and HR-user-side perceived quality of AI-supported recruitment where this paper tries to contribute.

Existing studies have substantially advanced knowledge on different aspects of algorithmic hiring risks as well as recruiter's trust or applicant fairness perceptions, AI adoption and auditability. However, limited evidence is available on whether the same explainability-based quality cue affects different dimensions of perceived AI quality in the same way, esp. among respondents with different levels of practical AI experience. Experience level in other digital domains has been shown to be a very crucial factor and changemaker in innovative adoption processes. In the paper, we understand perceived AI quality as a socio-technical evaluation of AI-supported recruitment decision support – whether the AI output is perceived as useful, understandable, trustworthy, controllable, usable and fair. The study addresses this gap by testing whether reasoning and confidence information operate as a universal quality signal, or rather as an experience-contingent cue whose effect differs between trust in use, willingness to use and fairness confidence.

3 CONCEPTUAL MODEL AND HYPOTHESES

The conceptual model distinguishes between an explainability-based quality cue, user-level practical AI experience and broader perceived-quality constructs of AI-supported recruitment. The survey examines AI-supported recruitment broadly, while the randomised scenario focuses on one concrete and sensitive decision-support situation: an AI-generated ranking of candidates for the next stage. This scenario was selected because ranking and prioritisation are recruitment tasks where explainability is particularly important for evaluating whether the AI output is understandable, credible, usable and fair. Explanation is operationalised as the presence of brief reasoning and confidence information attached to the AI

recommendation. The design follows recruitment and Explainable Artificial Intelligence (XAI) studies that use scenario-based designs to examine reactions to AI-supported hiring decisions and explanations (Gonzalez et al., 2022; Malin et al., 2025). Practical AI experience is treated as a potential moderator because prior exposure and maturity may change whether explanation is interpreted as a useful quality signal, a source of reassurance or an indication of the complexity of AI-supported recruitment decisions.

A key conceptual distinction is made between trust in use and fairness confidence. Trust in use refers to whether HR users consider AI output credible and usable for their decision or not. On the other hand, fairness confidence refers to the extent to which the AI-supported process is perceived as justifiable and acceptable from a candidate-centred perspective and from non-discriminatory aspect. These two aspects are related but not identical dimensions of perceived AI quality. A recruiter may trust a recommendation enough to use it as support for his decision, but may still not be sufficiently convinced if it treats candidate fairly. This distinction is in line with different studies where some results show that explainability may support interpretability and user trust, but fairness assurance requires more validation, human control or auditing (Kazim et al., 2021; Hunkenschroer & Kriebitz, 2023; Fabris et al., 2025). The hypotheses of this study are summarised in Table 1.

Table 1 – Hypotheses and analytical approach

Hypothesis	Expected relationship	Analytical test
H1	Explanation and confidence information improve evaluations of AI-supported candidate-ranking recommendations in recruitment.	Direct scenario effect on D1 trust, D2 willingness to use and D3 perceived fairness; Welch/Mann–Whitney tests and OLS with HC3 robust SE
H2	Practical AI experience positively moderates the effect of explanation and confidence information on trust in AI outputs.	Interaction model for D1; OLS with HC3 robust SE and ordered logit robustness check
H3	Practical AI experience positively moderates the effect of explanation and confidence information on willingness to use AI-supported recruitment.	Interaction model for D2; OLS with HC3 robust SE and ordered logit robustness check
H4	Practical AI experience moderates the effect of explanation and confidence information on perceived fairness.	Interaction model for D3; OLS with HC3 robust SE and ordered logit robustness check
H5	Perceived usefulness, trust, explainability and human control are positively associated dimensions of perceived AI quality in AI-supported recruitment.	Cronbach’s alpha for scale reliability; Spearman correlations among constructs; OLS models for intention to use
H6	HR professionals are more likely to accept full automation without human confirmation in administrative or support recruitment tasks than in sensitive autonomous candidate-affecting decisions.	Cochran’s Q, pairwise McNemar tests and descriptive acceptance rates

4 METHODOLOGY

4.1 Research Design and Data Collection

The empirical design combines a cross-sectional questionnaire survey with a randomised scenario-based module. The questionnaire examined perceived quality of AI-supported recruitment more broadly, including usefulness, trust, explainability, human control, fairness, privacy, organisational support, resistance, intention to use and perceived outcomes. The randomised scenario module focused on a concrete recruitment decision-support situation in which respondents evaluated an AI-generated ranking of candidates for the next stage, either without explanation or with explanation and confidence information. Scenario and vignette designs are common in studies of AI-supported hiring because they allow respondents to evaluate controlled recruitment situations while keeping the decision context understandable and comparable (Gonzalez et al., 2022; Malin et al., 2025).

The survey included questions on respondent, organisational and recruitment-context items, followed by branch-specific sections for respondents with and without practical AI experience to differentiate their perceptions and attitudes. In the scenario module, respondents were randomly assigned to one of two blocks. One group evaluated an AI-generated candidate ranking without explanation. The other group evaluated the same type of ranking with a brief AI-generated reasoning for the candidate order and confidence information about the recommendation. This design allows us to test whether explanation and confidence information operate as a perceived-quality cue and whether this effect differs based on respondent's practical AI experience.

The sample is interpreted as a purposive or convenience sample of HR-related professionals and it contained elements of a snowball survey approach. This approach has no ambition to achieve a statistically representative population and therefore limits generalisation. The survey was anonymous and did not systematically identify countries. Based on the distribution channels and response languages, the sample has a substantial Central European component (80+%). A condensed profile of the sample is provided in Table 2.

Table 2 – Condensed sample profile

Characteristic	Value	Characteristic	Value
Analytic sample	N = 145	Respondent role: Recruiter/ Talent Acquisition	31.0%
Start language: Slovak/Czech version	68.3%	Respondent role: Hiring manager	20.7%
Practical AI experience: Yes	54.5%	Respondent role: AI/IT support	13.1%
Scenario: explanation + confidence	55.9%	Respondent role: HR generalist	7.6%
Applicant Tracking System (ATS) use: Yes	46.9%	Respondent role: HR manager	12.4%

Characteristic	Value	Characteristic	Value
Formal AI policy: Yes/In preparation	49.7%	Respondent role: Other	15.2%
		Organisation size: 1–49	40.0%
		Organisation size: 50–249	8.3%
		Organisation size: 250–999	29.7%
		Organisation size: 1,000+	22.1%

4.2 Measures

The experimental treatment distinguished two AI candidate-ranking scenarios: (1) ranking without explanation and (2) ranking with brief AI-generated reasoning for the candidate order and confidence information about the recommendation. In this research, we measured three scenario outcomes: trust in the AI output, willingness to use such a tool and perceived fairness to candidates. This separation reflects prior literature indicating that explanation can influence perceived fairness and adoption, but that trust and willingness to rely on AI or fairness perceptions may be responded differently (Lacroux & Martin-Lacroux, 2022; Schoeffer et al., 2022; Malin et al., 2025).

The questionnaire generally included multi-item constructs measured on seven-point agreement Likert scales: perceived usefulness (PU), perceived ease of use (PEOU), trust and reliability (TR), explainability (EXPL), human control (CTRL), fairness/non-discrimination (FAIR), privacy/security (PRIV), organisational support (ORG), resistance/threat perception (RES), intention to use (INT), perceived outcomes (OUT) and satisfaction (SAT). Fairness and privacy combine perceived concerns with governance requirements related to non-discrimination, data protection and responsible AI use.

4.3 Analytical Procedure and Diagnostics

The analysis proceeded in six steps, where the first, sample characteristics and scenario allocation were described, and randomisation balance was assessed. Second, reliability was assessed using Cronbach's alpha and construct scores were computed as row means. Construct-level analyses used complete cases ($N = 141$), while the full analytic sample was $N = 145$. Third, Spearman correlations were used to examine construct relationships because ordinal character and not assumed to be normally distributed. Fourth, Welch tests, Mann-Whitney U tests and OLS models with HC3 robust standard errors were used to estimate scenario effects and moderation by practical AI experience. Fifth, ordered logit models were used as robustness checks for ordinal scenario outcomes, and variance inflation factors (VIF) were used to assess collinearity. Finally, automation acceptance was analysed using Cochran's Q/McNemar tests, complemented by exploratory segmentation trees and an exploratory predictor heatmap based on task-specific binary models. The diagnostic and robustness checks are reported in Table 3.

Table 3 – Diagnostic and robustness checks

Check	Result	Interpretation
Construct reliability	PU = 0.903; TR = 0.818; EXPL = 0.812; CTRL = 0.825; INT = 0.925	Core scales show good to excellent internal consistency.
Scenario model VIF	max VIF = 3.71	No critical multicollinearity in interaction models.
Construct model VIF	max VIF = 2.60	No critical multicollinearity in quality-predictor models.
Heteroskedasticity	Breusch-Pagan $p < 0.01$ in OLS models	HC3 robust standard errors used.
Ordinal robustness	Ordered logit significant for D1 interaction only	Trust moderation is the most robust scenario result.
Automation-choice dependence	Cochran Q = 170.8, $p < 0.001$; McNemar $p < 0.001$	Acceptance varies sharply by task; autonomous candidate rejection is the least accepted option.

5 RESULTS

First, we assessed measurement quality and construct relationships. Then, scenario effects and moderation by practical AI experience were tested, followed by a differentiated interpretation of trust, willingness and fairness. After reporting construct-level predictors and mediation results, automation boundaries and trust-building requirements are analysed. Finally, exploratory non-linear segmentation is used to illustrate configurations associated with high intention to use AI.

5.1 Measurement Quality and Construct Relationships

The empirical design combines a cross-sectional questionnaire survey with a randomised scenario-based between-subjects module. The questionnaire examined perceived quality of AI-supported recruitment in terms of usefulness, trust, explainability, human control, fairness, privacy, organisational support, resistance, intention to use and perceived outcomes.

As shown in Table 4, the multi-item constructs demonstrate satisfactory reliability. Perceived usefulness, trust and reliability, explainability, human control and intention to use AI achieved alpha values above the conventional 0.80 threshold. Lower-reliability or conceptually mixed constructs were retained for cautious exploratory interpretation while fairness and privacy we interpreted as conceptually distinct concern/governance components.

Table 4 – Reliability and descriptive statistics for core constructs

Construct	Items	N	Cronbach's alpha	M	SD
PU	3	141	0.903	5.72	1.14
PEOU	2	141	0.777	5.59	1.05
TR	3	141	0.818	5.04	1.03
EXPL	2	141	0.812	5.46	1.01
CTRL	2	141	0.825	5.98	0.98
RES	2	141	0.616	3.91	1.37
INT	2	141	0.925	5.77	1.12
OUT	2	141	0.716	5.28	1.16
SAT	1	141	n/a	5.36	1.06

Note: Cronbach's alpha reports internal consistency; M = mean; SD = standard deviation; n/a = not applicable for a single-item measure.

The main correlations among the perceived-quality constructs are summarised in Table 5.

Table 5 – Selected Spearman correlations among perceived-quality constructs

Relationship	Spearman rho
PU – OUT	0.751***
PU – INT	0.648***
TR – SAT	0.758***
TR – INT	0.627***
EXPL – TR	0.580***
EXPL – CTRL	0.593***
CTRL – INT	0.431***
RES – TR	-0.385***

5.2 Scenario Effects and Moderation Analysis

The moderation results are reported in Table 6 and show that the direct comparison between the two scenarios did not support a simple universal explanation effect. Mean trust was slightly higher in the explanation scenario, while willingness and perceived fairness were slightly lower. However, none of these direct differences was statistically significant. The stronger statistical evidence appears in the moderation models, where practical AI experience changes how explanation and confidence information are interpreted.

Table 6 – Moderation by practical AI experience: explanation x AI experience

Outcome	Interaction coefficient (b)	SE	95% CI low	95% CI high	p	R ²
Trust in AI outputs	1.18	0.487	0.225	2.13	0.015	0.141
Willingness to use	0.930	0.427	0.093	1.77	0.029	0.161
Perceived fairness	0.675	0.499	-0.304	1.65	0.176	0.048

Note: Regression coefficients are unstandardised coefficients. Robust p-values are based on HC3 standard errors. R² denotes the coefficient of determination.

Figure 1 illustrates the scenario-response patterns by practical AI experience. The interaction was strongest for trust in AI outputs. Explanation and confidence information work as a credibility cue mainly for respondents with practical AI experience. This is consistent with research suggesting that trust in AI decision support is shaped not only by the presence of an algorithmic recommendation but also by users' ability to interpret and calibrate the recommendation (Lacroux & Martin-Lacroux, 2022; Schoeffer et al., 2022).

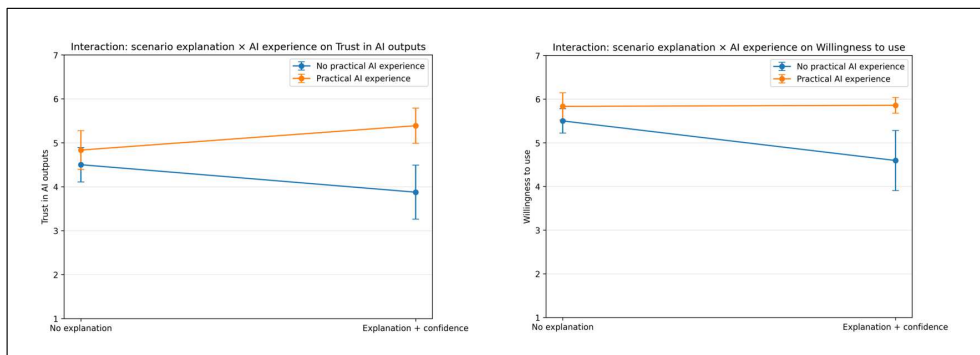


Figure 1 – Scenario response patterns for trust and willingness by practical AI experience

For respondents without practical AI experience, explanation may not yet function as reassurance; it may instead highlight the complexity and uncertainty of AI-supported ranking. A differentiated interpretation of these scenario outcomes is provided in Table 7.

Table 7 – Differentiated interpretation of scenario outcomes

Outcome	Interpretation	b	p	Ordinal p	Managerial meaning
Trust in AI outputs (D1)	Trust in use / credibility of AI output	1.18	0.015	0.007	Experienced users interpret explanation and confidence as a credibility cue that makes the ranking more usable as decision support.
Willingness to use (D2)	Adoption readiness	0.930	0.029	0.349	A similar pattern appears, but robustness is weaker under ordinal modelling; interpreted as a managerial pattern rather than the strongest statistical result.
Perceived fairness (D3)	Fairness confidence / perceived non-discrimination	0.675	0.176	0.442	The same explanation cue does not statistically convince respondents that the ranking is fair; fairness remains a separate assurance issue.

The pattern is managerially important. An experienced HR professional may say: “I understand why AI ranked this candidate higher. The explanation and confidence score help me trust the recommendation enough to use it as decision support.” However, the same professional may still add: “This explanation does not convince me that the ranking is fair to all candidate groups.” The first statement concerns trust in use and operational understanding; the second concerns fairness confidence. The non-significant fairness moderation therefore does not simply mean that fairness is an uninteresting outcome. It suggests a stronger implementation warning: explanation and confidence information may make an AI recommendation more usable without making it perceived as fair. Fairness therefore requires independent validation, bias testing and auditability.

5.3 Construct-level Regression and Mediation Analysis

The multivariable regression results are presented in Table 8.

Table 8 – Construct-level regression models with HC3 robust standard errors

Model	Predictor	b	SE	p	R ²	N
TR model	EXPL	0.350	0.095	0.000	0.475	141
TR model	PU	0.184	0.068	0.007	0.475	141
TR model	PEOU	0.279	0.110	0.011	0.475	141
TR model	ai_experience	0.178	0.134	0.183	0.475	141
INT model	TR	0.472	0.105	0.000	0.636	141
INT model	PU	0.255	0.088	0.004	0.636	141
INT model	CTRL	0.227	0.080	0.004	0.636	141
INT model	ai_experience	0.547	0.138	0.000	0.636	141

Model	Predictor	b	SE	p	R ²	N
INT extended	TR	0.481	0.107	0.000	0.641	141
INT extended	PU	0.269	0.083	0.001	0.641	141
INT extended	CTRL	0.242	0.075	0.001	0.641	141
INT extended	RES	0.058	0.043	0.175	0.641	141
INT extended	ai_experience	0.510	0.136	0.000	0.641	141

Note: Regression coefficients are unstandardised coefficients. Robust p-values are based on HC3 standard errors. R² denotes the coefficient of determination.

Construct-level models also support the multi-dimensional interpretation of perceived AI quality. Trust and reliability were predicted by parameters of explainability, perceived usefulness and ease of use. The parameter intention to use AI was predicted by trust, perceived usefulness, human control and practical AI experience. Bootstrap mediation, as presented in Table 9, indicated that trust really partially mediated the association between explainability and intention to use AI, controlling for perceived usefulness and AI experience.

A similar indirect association was found also for human control through trust. These findings support the interpretation that trust is an important transmission mechanism in this decision making area, but it is not the only requirement for quality-oriented implementation.

Table 9 – Bootstrap mediation results

Path	N	Indirect effect	95% CI low	95% CI high	Bootstrap p
EXPL → TR → INT	141	0.187	0.094	0.294	0.000
CTRL → TR → INT	141	0.130	0.042	0.195	0.008

5.4 Automation Acceptance and Implementation Requirements

The practical module shows a sharp boundary between accepted automation and rejected autonomous decision-making. Full automation without human confirmation was most often accepted for job-posting text generation, candidate outreach and interview scheduling, but was rarely accepted for ranking without approval and almost never accepted for automatic candidate rejection. This is aligned with existing literature on augmented hiring, where these studies show more favourable reactions of users when AI assists humans rather than replaces them in sensitive candidate-affecting selection decisions through full automation (Gonzalez et al., 2022; Hunkenschroer & Kriebitz, 2023).

Figure 2 summarises automation acceptance and the main trust-building requirements.

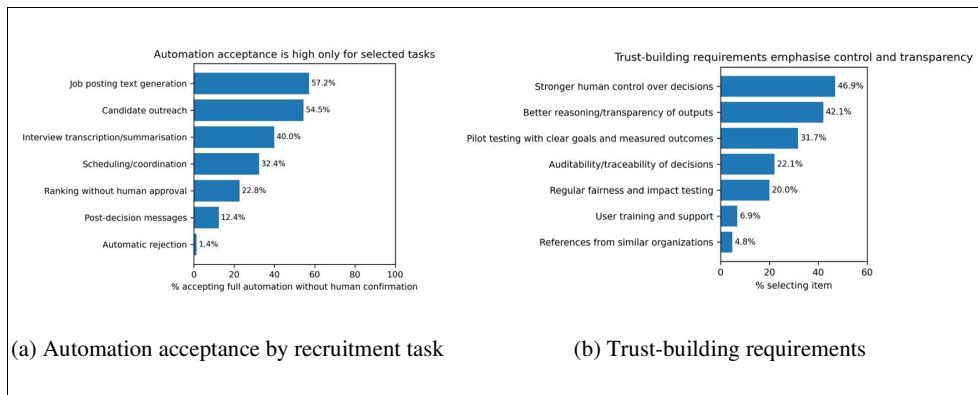


Figure 2 – Automation acceptance and trust-building requirements

Using Cochran's Q we confirmed that acceptance differed significantly across tasks. The McNemar comparison between job-posting automation and automatic candidate rejection was highly significant. The most frequently selected trust-building requirement was stronger human control, followed by reasoning/transparency and pilot testing with measured outcomes.

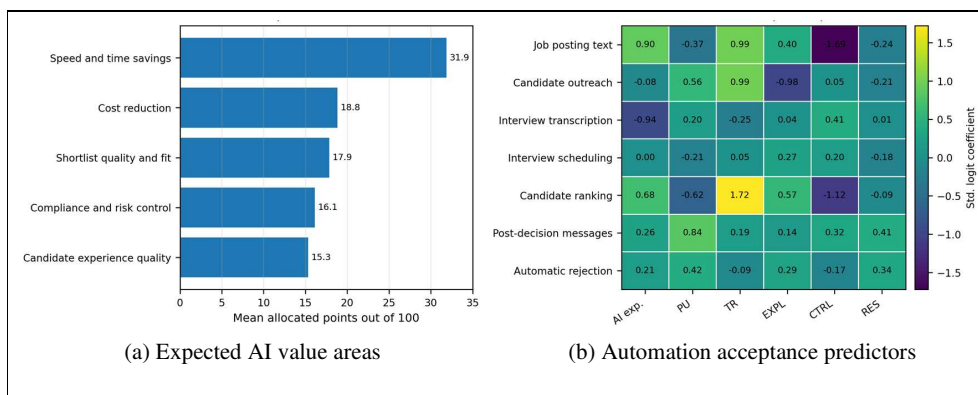


Figure 3 – Expected value allocation and exploratory predictors of automation acceptance

These tests support general findings in a human-centred quality-management interpretation in which AI is acceptable when it augments human work and remains controllable, but less acceptable when it replaces accountability in sensitive candidate-affecting decisions.

When analysing an expected value allocation (Figure 3a), we have found that respondents see AI value primarily in speed and time savings, but not only in efficiency. Shortlist quality, cost reduction, compliance/risk control and candidate experience also received substantial allocations. The exploratory predictor heatmap in Figure 3b summarises standardised coefficients from task-specific regularised logistic models of full-automation acceptance. It illustrates how

automation preferences are associated with perceived usefulness, trust, explainability, human control, resistance and practical AI experience across recruitment tasks.

5.5 Exploratory segmentation analysis

A parsimonious classification tree, presented in Figure 4, was estimated as an exploratory visual explanation of high intention to use AI ($INT \geq 6$). The tree should be interpreted cautiously due to the sample size, but it provides a useful managerial segmentation. The first-strongest split was human control. High intention was concentrated among respondents who perceived both strong human control and high usefulness. In the intermediate group with high control but lower usefulness, the explanation-and-confidence scenario was associated with a higher share of high intention, suggesting that explanation may help only after minimum control conditions.

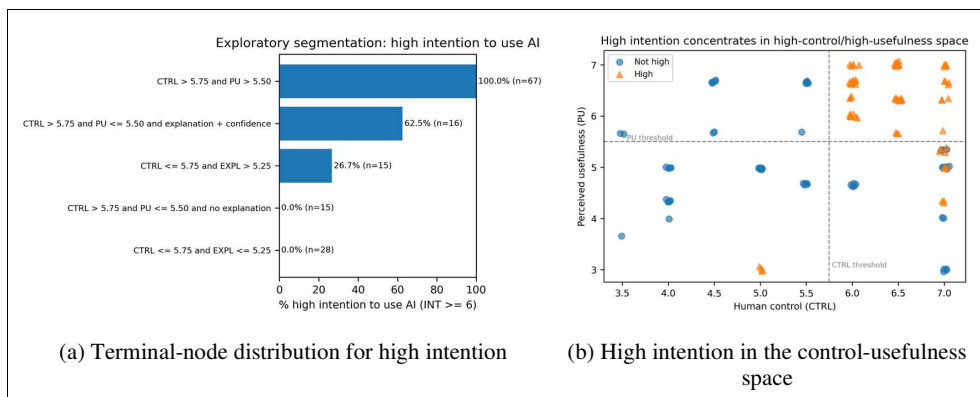


Figure 4 – Exploratory segmentation of high intention to use AI

6 DISCUSSION

Before interpreting the findings in managerial terms, Figure 5 summarises the empirically supported and unsupported relationships. The scheme is presented as an ex-post synthesis of the results, not as an a priori structural model.

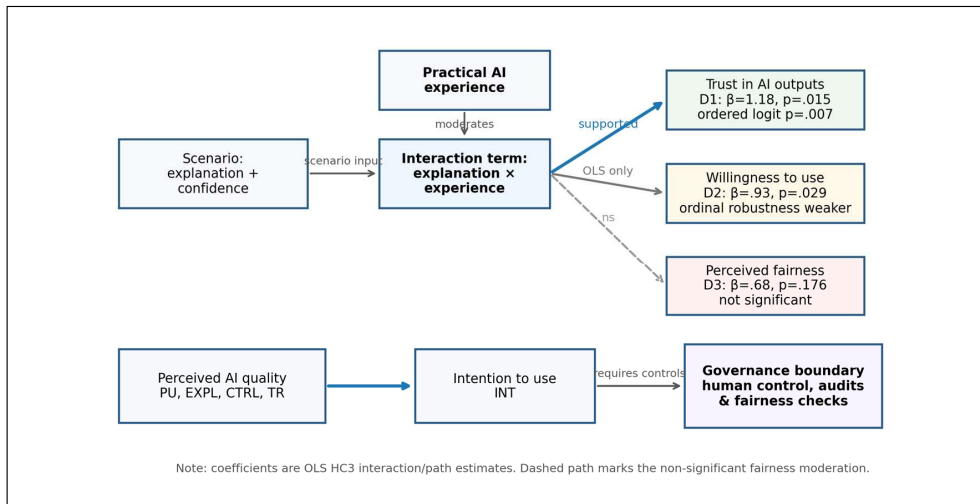


Figure 5 – Empirical synthesis of supported and unsupported relationships

6.1 Interpretation of Moderation Effects

The results challenge the assumption that adding explanation and confidence information automatically increases perceived quality of AI-supported recruitment. The direct scenario effect was not significant. The key statistical result is the moderation pattern. It supports the argument, that practical AI experience changes how explanation is interpreted, especially for trust in AI outputs. It means, explanation is not a universal quality signal. It becomes a quality cue only when users can relate it to their own mental model, domain knowledge and calibration of AI limitations (Schoeffler et al., 2022; Lacroux & Martin-Lacroux, 2022).

This finding has practical implications for AI implementation. Explainability should not be deployed as a stand-alone feature or as a pro-forma transparency layer. It should be embedded in training, examples, calibration exercises and pilot feedback so that users can learn when to follow AI recommendations, when to challenge them and finally how to interpret confidence information. This corresponds to quality-oriented implementation logic from different studies, where AI-enabled decision support requires people capability, leadership, process integration and data governance, not only some technical functionality (Sony et al., 2020; Carvalho et al., 2024).

6.2 Fairness as a Distinct Assurance Dimension

The most important conceptual contribution concerns the difference between trust in use and fairness confidence. Trust and willingness to use are user-side adoption perceptions: they indicate whether HR professionals find AI recommendations credible, useful and operationally acceptable. Fairness is a harder assurance dimension: it concerns whether the system is perceived as valid, non-discriminatory and procedurally just from the candidate's point of view. The

empirical result does not prove that respondents believed the AI was unfair. It shows a more precise and practically relevant point: the explanation and confidence cue did not convince them that the AI-supported ranking was fair. Algorithmic hiring research similarly shows that fairness cannot be inferred from local explanation alone; it requires auditing, bias testing, governance and evidence across groups and cases (Kazim et al., 2021; Fabris et al., 2025).

A practical example illustrates the point. An experienced HR user may say: “I understand why AI ranked this candidate higher. The explanation and confidence score help me trust the recommendation enough to use it as decision support.” However, the same user may not be willing to say: “I am convinced that this ranking is fair to all candidate groups.” This difference is not only a knowledge gap. It is a fairness-confidence gap. It captures the empirical pattern of the study: explanation can support experienced-user trust, while perceived fairness remains insufficiently improved by the same explanation cue.

An AI system may explain that a candidate was ranked higher because of relevant experience, skill overlap and role fit. This may help an experienced HR user understand the ranking and accept it as a decision-support input in the decision making process. However, we have to be careful also in this aspect, as this doesn’t demonstrate whether years of experience penalise career breaks, whether prior employer prestige proxies social background or whether model errors differ across groups. This should be examined in further research on larger samples to identify more complex patterns. In quality-management terms, AI explanations improve local interpretability of an output, whereas fairness confidence requires a system-level quality control and governance process.

6.3 Human Control and Acceptable Automation Boundaries

The results on full automation opportunities show that respondents do not generally reject AI automation. They differentiate between tasks with lower decision-finality and tasks that directly affect candidate outcomes and are more sensitive. Acceptance was highest for job-posting text generation and candidate outreach, but the interpretation of job-posting automation must remain cautious. If respondents understood the task as drafting or stylistic support based on human-defined requirements, the risk is lower. If they understood it as AI autonomously defining role requirements and publishing vacancies, the risk would be much higher. The current item cannot fully separate these interpretations.

The almost complete rejection of automatic candidate rejection without human approval is one of the clearest managerial results. It indicates that HR professionals draw a boundary around sensitive autonomous organisational decisions. This boundary is consistent with the trust-building responses.

6.4 Implications for Quality-oriented AI Implementation in HR

We can find four recommendations for the world of HR practice. AI implementation in HR should begin with tasks where perceived value is high and decision-finality is lower. Organisations should clearly distinguish between drafting support and autonomous publication or rejection to increase trust and willingness of AI users. AI explanations or reasoning features should be also designed differently for different levels of user maturity. Experienced users may benefit from concise reasoning and confidence indicators, while less experienced users may require training, use cases or examples and calibration feedback to improve their awareness and readiness to work with AI tools efficiently.

Together, we consider as very interesting and critical result in governance implication area. Fairness assurance must be separated from trust-building. Explanations and confidence scores may make AI recommendations more understandable and usable for experienced HR users, but they do not by themselves demonstrate that the underlying ranking is fair. This creates a practical risk that organisations may become comfortable relying on AI-supported recommendations before they have sufficient evidence that the systems are fairness-assured. Therefore, explainability should be complemented by independent bias testing, auditability and fairness governance. Impact of these results can be significant, as it can develop bias in AI hype era and can bring high risks for whole society and in AI adoption area generally.

Finally, AI-supported recruitment should be managed as a quality-controlled organisational process in which efficiency, decision quality, human control, candidate experience, auditability and social responsibility are treated as interconnected quality requirements.

7 CONCLUSION

This paper examined perceived quality of AI-supported recruitment through the lens of explainability, trust and human control. Based on relevant literature, the study shows that explanation and confidence information do not create a uniform improvement in evaluations of AI candidate ranking. Instead, they operate as explainability-based quality cues whose effect depends on practical AI experience, with the strongest and most robust effect observed for trust in AI outputs.

The research further shows that intention to use AI is associated with trust, perceived usefulness, human control and prior AI experience. Regarding automation acceptance, the results show that HR professionals accept AI support mainly in selected non-sensitive support tasks and reject autonomous candidate rejection because of the risk of discriminatory or unfair results. These results support a configurational view of AI quality in recruitment. Explainability matters, but it matters together with user experience, usefulness, control and governance. The distinctive finding is that explanation may strengthen trust in use without

increasing fairness confidence. Fairness remains a distinct assurance problem that requires independent validation beyond explanation.

We encourage researchers in future studies to test these relationships in larger and more representative samples, distinguish different levels of AI support in job-ad generation and connect perceived quality with objective indicators of model performance, fairness, bias and candidate outcomes. Specific attention should be paid to the trust–fairness gap identified in this study, especially to whether explanation-induced usability can encourage premature organisational reliance on AI-supported decisions before fairness and group-level validity have been independently audited.

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ABOUT AUTHORS

Coi Tran ORCID: 0000-0002-7947-0907 (C.T.) – Doctoral researcher, his research focuses on applications of AI in HR, Department of Banking and Investment, Faculty of Economics, Technical University of Kosice, Košice, Slovakia, e-mail: coit@fpt.com.

Radoslav Delina ORCID: 0000-0003-0412-9840 (R.D.) – Prof., his research focuses on complex decision automation and intelligence in business processes, Department of Banking and Investment, Faculty of Economics, Technical University of Kosice, Košice, Slovakia, e-mail: radoslav.delina@tuke.sk.

AUTHOR CONTRIBUTIONS

Conceptualisation, R.D.; Methodology, R.D.; Formal analysis, C.T.; Investigation, C.T.; Original draft preparation, C.T.; Review and editing, R.D. and C.T.; Supervision, R.D.; Project administration, R.D.

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