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RESEARCH ARTICLE

An integrated partial least squares structural equation modeling, artificial neural network, and importance–performance map analysis framework for Industry 4.0 readiness in university startups

Syed Rizwan Ali[1]*, Muhammad Irfan Memon[2]*, Mohammad Mohatram[2], Muhammad Faraz[2,3], Muhammad Mumtaz Khan[2,3], and Javeed Hussain[2]

[1]Department of Business Incubation Center & Software Engineering, Bahria School of Engineering and Applied Sciences, Bahria University, Karachi, Sindh, Pakistan

[2]Department of Electrical and Electronics Engineering, Global College of Engineering and Technology, Muscat, Oman

[3]Department of Business Studies, Bahria Business School, Bahria University, Karachi, Sindh, Pakistan

rizwanali.bukc@bahria.edu.pk, m.memon@gcet.edu.om, m.mohatram@gcet.edu.om, mfaraz.bukc@bahria.edu.pk, mumtazned1@yahoo.com, s.javeedhussain@gcet.edu.om

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ABSTRACT

Since Industry 4.0 entered international policy and scholarly debate in 2011, the convergence of cyber-physical systems, the Internet of Things, cloud computing, data analytics, artificial intelligence, and intelligent automation has reshaped how university-linked startups are conceived, incubated, and scaled. This study evaluates an integrated partial least squares structural equation modeling (PLS-SEM), artificial neural network (ANN), $PLS_{predict}$/cross-validated predictive ability test (CVPAT), and importance–performance map analysis (IPMA) framework linking technological infrastructure (TI), innovation capacity (IC), entrepreneurship education (EE), digital capability (DC), and Industry 4.0 readiness (I4R). A quantitative cross-sectional survey using criterion-based purposive sampling produced 250 usable responses from student entrepreneurs, incubator resident venture representatives, faculty startup advisers, and innovation center employees. PLS-SEM with 5,000 bootstrap resamples showed that DC had the strongest positive association with I4R ($\beta = 0.485$, $p < 0.001$), followed by TI ($\beta = 0.241$, $p < 0.001$). EE showed a small, marginally significant positive association ($\beta = 0.095$, $p = 0.047$), whereas IC was not significant ($\beta = 0.083$, $p = 0.093$). The model explained 53.8% of the variance in I4R ($R^2 = 0.538$). $PLS_{predict}$ yielded positive $Q^2_{predict}$ values for all I4R indicators, and construct-level CVPAT showed significantly lower PLS-SEM prediction loss than the linear-model benchmark (difference = –0.059, $t = 2.602$, $p = 0.010$). A fully specified, repeated cross-validated multilayer perceptron ANN ranked DC first (100% normalized importance), followed by TI (47.6%), EE (10.9%), and IC (10.0%); however, the matched linear benchmark achieved lower held-out root mean square error, so ANN is interpreted as a complementary ranking tool rather than evidence of superior predictive accuracy. IPMA identified DC (importance = 0.485; performance = 48.222) and TI (0.241; 46.037) as the leading intervention priorities. The framework therefore integrates explanatory assessment, out-of-sample prediction, predictive ranking, and intervention prioritization without implying causal proof from cross-sectional data.

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1. Introduction

Industry 4.0 was introduced publicly at Hannover Messe in 2011 and consolidated through the German Industrie 4.0 initiative in 2013.[1] In the literature, it denotes the digitally enabled integration of cyber-physical systems, Internet of Things (IoT), cloud platforms[2], data analytics, artificial intelligence (AI), and intelligent automation across organizational and value-creation processes.[2,3] In this article, Industry 4.0 readiness (I4R) means the capacity of university startups and their supporting institutions to combine infrastructure, entrepreneurial learning, innovation processes, and digital capability (DC) for technology-enabled venture development. This setting differs from established small- and medium-sized enterprises (SMEs) because resources are often institutionally shared, ventures are early-stage, and readiness depends on interaction among students, faculty advisers, incubators, and innovation-center personnel.[4] The article therefore treats readiness as an ecosystem-level capability rather than solely as a firm-level technology-adoption condition.

Despite the growing relevance of Industry 4.0, many university-based startups face fragmented digital skills development, limited technological infrastructure (TI), uneven access to decision-support tools, and few structured processes for assessing readiness.[5,6] Existing assessments often rely on qualitative descriptions or narrow indicators that do not capture the interrelated educational, technological, organizational, and capability dimensions of readiness.[7,8] This creates a practical need for an integrated assessment that can estimate relationships, identify capability gaps, and prioritize interventions without implying causal proof from cross-sectional data.

Previous studies have separately investigated discrete factors influencing digital transformation readiness. For example, entrepreneurship education (EE) has been cited as essential to enhancing students' innovation-oriented behavior and technology usage for entrepreneurial purposes.[8,9] Similarly, TI, incorporating elements such as equipment, software, communications capabilities, and digital platform services, has been shown to positively influence the DC development of early-stage firms.[10,11] Furthermore, innovation capacity (IC), understood as an organization's capability to create novel products/ideas and to bring them to market, has also been noted as having an impact on digital transformation success.[12-14] However, while these antecedents have each been individually demonstrated to contribute toward digital transformation readiness in university startup environments, they have seldom been assessed in conjunction with one another in a single empirical study.[15]

This study addresses this gap by developing and evaluating an integrated partial least squares structural equation modeling (PLS-SEM), artificial neural network (ANN), $PLS_{predict}$/ cross-validated predictive ability test (CVPAT), and importance–performance map analysis (IPMA) framework for I4R assessment.[16] PLS-SEM estimates the unique direct associations of TI, IC, EE, and DC with readiness; $PLS_{predict}$ and CVPAT assess out-of-sample predictive performance[17]; ANN provides a complementary ranking of predictor importance; and IPMA combines importance with performance to identify intervention priorities.[18] The theoretical contribution is a comparative ecosystem-level assessment of technological, educational, innovation, and DC antecedents of readiness.

The practical contribution is a transparent basis for prioritizing capability and infrastructure interventions. The framework is analytical rather than a new AI algorithm, autonomous optimization system, or deployable software application.

1.1. Research questions

This study is guided by the following research questions (RQs):

(i) RQ1: How is TI associated with I4R?
(ii) RQ2: Is IC significantly associated with I4R?
(iii) RQ3: How is EE associated with I4R?
(iv) RQ4: What is the association between DC and I4R?
(v) RQ5: How well does the PLS-SEM model predict I4R out of sample relative to benchmark models?
(vi) RQ6: Which factors rank highest in ANN predictive importance, and which constructs and indicators represent the highest IPMA intervention priorities?

1.2. Research objectives

In alignment with the research questions above, this study pursues the following specific research objectives (ROs):

(i) RO1: Estimate the unique direct associations of TI, IC, EE, and DC with I4R using PLS-SEM.
(ii) RO2: Assess the explanatory power, effect

sizes, collinearity, and out-of-sample predictive performance of the I4R model.
(iii) RO3: Assess predictor importance using a repeated-cross-validated ANN model based on SmartPLS latent-variable scores.
(iv) RO4: Use construct- and indicator-level IPMA to identify priority areas for improving I4R.
(v) RO5: Integrate the PLS-SEM, predictive, ANN, and IPMA findings into an evidence-based intervention-prioritization framework.

2. Literature review

2.1. Industry 4.0 and university startup ecosystems

The adoption of Industry 4.0, which integrates advanced manufacturing techniques with digital intelligence to create unprecedented levels of automation, customization, and interconnectedness, presents both opportunities and imperatives for university startup ecosystems.[19,20] Startups that are unable to achieve even minimal digital preparedness will continue to become obsolete at increasing rates, while those that successfully integrate AI, IoT, and data analytics capabilities will gain sustainable competitive advantages.[21,22] Industry 4.0 represents an essential competency for universities seeking to establish successful incubators for startup businesses. According to Samo *et al.*[23], the effectiveness of university-based startup incubation is highly dependent upon the ability of the startup ecosystem to bridge academic knowledge with Industry 4.0-related competencies such as digital production, smart decision-making, and platform-based business models.

Despite the growing number of I4R frameworks since the mid-2010s, most have focused on manufacturing organizations rather than academic startups.[7] Existing academic-entrepreneurship frameworks also rely heavily on conceptual, expert-judgment, or qualitative approaches.[24] The present study addresses this gap by quantitatively testing a readiness model tailored to university startup ecosystems.[3]

At the ecosystem level, I4R depends on more than the availability of digital tools. Muldoon-Smith *et al.*[4] show that digital innovation relies on sociotechnical knowledge-transfer pipelines in which tacit knowledge is translated across institutions and communities. Göçoğlu *et al.*[25] similarly demonstrate that AI-oriented innovation is conditioned by research and development investment and the characteristics of the surrounding urban context. Practice-based evidence from the URBACT AS TRANSFER network indicates that effective startup boosting combines needs diagnosis, entrepreneurship learning, staged training, prototyping, market validation, incubation, and partnership brokering.[26] Recent work on emerging economies also situates digital entrepreneurship and startup-ecosystem development within the broader Industry 4.0 transition.[27] Collectively, this literature supports an ecosystem-level readiness model integrating technological, educational, organizational, and capability dimensions. Because the *SSRN* source is a non-peer-reviewed working paper, it is used here only as emerging contextual evidence.

University startup ecosystems are theoretically distinct from conventional SMEs and general EE settings in three ways. First, access to technology is often mediated by university infrastructure rather than owned by the venture. Second, capability development is shared across students, faculty advisers, incubator managers, and innovation-center staff. Third, many ventures are pre-revenue or early-stage and combine learning, experimentation, and commercialization simultaneously. These features justify testing an ecosystem-level resource-learning-capability model instead of transferring an SME readiness framework without contextual adaptation. **Table 1** summarizes the principal prior studies and identifies the research gap addressed by the integrated framework.

2.2. Entrepreneurship education and digital capability

Entrepreneurship education comprises formal and informal educational experiences in which individuals acquire entrepreneurial knowledge, attitudes, and skills.[28] In the context of Industry 4.0, EE has expanded from traditional business plan modules to include digital literacy, technology commercialization, platform economics, and AI-assisted decision-making.[9,29,30] Research confirms that university programs incorporating technology-based learning generate graduate students who possess significantly greater levels of digital preparedness compared to graduates from university programs that do not incorporate technology-based learning.[6,23] EE may enhance readiness through the DCs that its educational experiences help develop.[24,31]

Digital capability is the ability of startup founders and teams to use digital technologies

Table 1. Summary of prior studies on Industry 4.0 and university startup ecosystems

Study	Focus	Method	Key Finding
4	Sociotechnical knowledge transfer	Conceptual analysis	Tacit and explicit knowledge must be translated across institutions for digital innovation
9	Industry 4.0 startup education	Design-based study	A tailored university course improved Industry 4.0 knowledge and perceived behavioral control
15	Industry 4.0 readiness & barriers	Empirical survey	Infrastructure and skills are dominant readiness drivers
21	University 4.0 essentials	Conceptual review	HEIs require ecosystem-level transformation for Industry 4.0
23	University entrepreneurial ecosystems	Case study	Synchronization between universities and Industry 4.0 is lacking
25	AI innovation and urban context	Quantitative urban analysis	AI-oriented innovation is shaped by R&D investment and metropolitan conditions
26	Startup boosting in an Industry 4.0 context	Practice-based thematic report	Staged learning, validation, incubation, and partnerships support startup development

Abbreviations: AI: Artificial intelligence; HEI: Higher education institution; R&D: Research and development.

for value creation, operational improvement, and innovation.[31] Drawing on dynamic capability's theory[32] and digital transformation research, DC is treated as a proximal organizational capability that reflects the ability to deploy digital resources in practice. In the present model, DC is assessed alongside TI, EE, and IC as a direct antecedent of I4R rather than as a mediator. This parallel specification allows the unique readiness association of each construct to be estimated while controlling for the others.

2.3. Technological infrastructure and innovation capacity

Technological infrastructure refers to the hardware, software, networks, cloud computing, data-management systems, and digital platforms available to university startups through their institutional environments.[24] Prior research consistently identifies infrastructure access as an important facilitator of digital transformation and Industry 4.0 preparedness.[7,8,24] In university startup ecosystems, where ventures often depend on shared institutional resources, stronger TI is therefore expected to be positively associated with I4R.[3]

Innovation capacity is the organization's ability to conceptualize and test ideas, recombine knowledge, and develop novel products or services.[5,12,33,34] Although IC is theoretically relevant to digital transformation, its unique association with readiness may weaken when technology access, EE, and DC are considered simultaneously. The present model therefore tests IC as a direct antecedent of I4R rather than whether IC necessarily translates into digital readiness. **Table 2** defines the five constructs, their abbreviations, conceptual meanings, and theoretical foundations.

3. Proposed model and methodology

3.1. Conceptual framework and hypotheses

The framework models TI, IC, EE, and DC as four parallel antecedents of I4R. Resource-based reasoning supports TI as an enabling technology resource, human-capital reasoning supports EE as a capability-building input, innovation research motivates IC, and dynamic capabilities theory supports DC as the ability to deploy digital resources for value creation. Estimating the four constructs simultaneously permits comparison of their unique associations with readiness within a university startup ecosystem.

The direct effects specification is intentionally parsimonious. TI captures access to digital infrastructure, EE captures entrepreneurial

Table 2. Summary of key constructs and measurement bases

Construct	Abbreviation	Conceptual definition	Theoretical basis
Technological infrastructure	TI	Hardware, software, digital platforms available to startups	Resource-based view; Industry 4.0 readiness models
Innovation capacity	IC	Organizational ability to generate and exploit novel ideas	Dynamic capabilities theory
Entrepreneurship education	EE	Formal/informal learning enabling entrepreneurial action	Human capital theory
Digital capability	DC	Competence to deploy digital technologies for value creation	Digital transformation literature
Industry 4.0 readiness	I4R	Overall preparedness for Industry 4.0 adoption and digital transformation	Industry 4.0 maturity frameworks

learning, IC captures ideation and experimentation capability, and DC captures the capacity to deploy digital technologies. Each construct may contribute to readiness through a distinct mechanism, but the cross-sectional design does not establish temporal or causal ordering. The model therefore evaluates theory-consistent associations and relative predictive importance rather than causal pathways.

An alternative mediation model places DC between TI/IC/EE and I4R. The parallel direct-path model was adopted during revision because resource-based, human capital, innovation, and dynamic capability perspectives also allow infrastructure, entrepreneurial learning, and IC to relate to readiness independently of DC. The revised model is not presented as prespecified before reanalysis. Because the survey measured all constructs once, the temporal order needed to support a causal mediation interpretation cannot be established. The mediation model remains plausible, but it has not been re-estimated with the same 250 responses. **Figure 1** presents the proposed structural model of direct effects and the four hypothesized relationships with I4R.

Based on this theoretical foundation, four hypotheses were formulated:

(i) H1: TI is positively associated with I4R.
(ii) H2: IC is positively associated with I4R.
(iii) H3: EE is positively associated with I4R.
(iv) H4: DC is positively associated with I4R.

3.2. Research design and sampling

This study used a quantitative, cross-sectional survey design. Because the research required participants with direct knowledge of university startup support and digitalization, the study used non-probability, criterion-based purposive sampling. Eligibility required at least six months of direct involvement as a student entrepreneur, a representative of an incubator-resident venture, a faculty member advising entrepreneurial ventures, or an innovation center employee. Data were collected from March to May 2025 at three university-linked incubators in Karachi, Pakistan. The sites were designated as Incubators A, B, and C because their identities and identifying details were subject to institutional confidentiality restrictions. Of 400 distributed questionnaires, 250 usable responses were retained, giving a 62.5% usable response rate. The final sample comprised 48% student entrepreneurs, 27% incubator-resident representatives, 15% faculty advisers, and 10% innovation-center employees. The individual participant was the unit of analysis. Role membership was recorded, and the groups were pooled for the primary model because all participants had at least six months of direct involvement in university startup activities and answered the same questionnaire about this setting. Students, venture representatives, faculty advisers, and innovation-center staff offer complementary perspectives on shared ecosystem resources and capabilities. The pooled coefficients describe associations across these sampled perceptions; common involvement and item wording do not establish equivalent construct interpretation or role-specific relationships.

The questionnaire contained 25 reflective indicators, with five items for each construct,

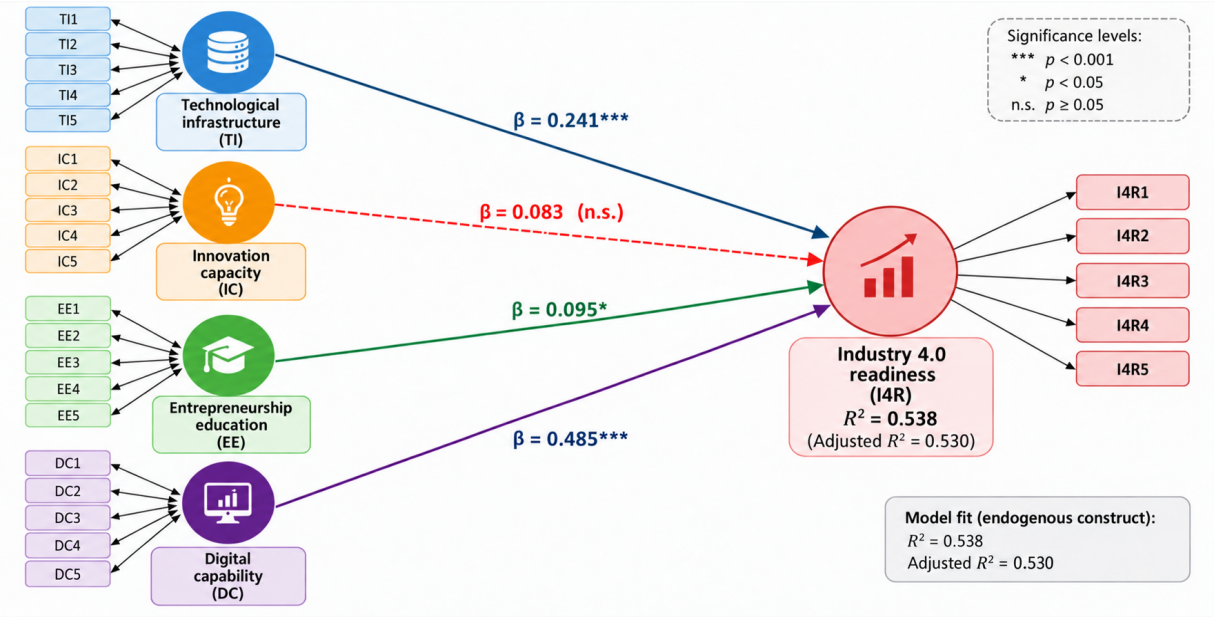


Figure 1. Integrated Industry 4.0 readiness framework
Notes: TI, IC, EE, and DC are modeled as parallel antecedents of I4R. Hypothesized paths are tested using partial least squares structural equation modeling, and all subsequent predictive and priority analyses use the same direct-effects specification.

measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). Measurement domains were aligned with prior I4R research for TI and I4R[7,15], university entrepreneurship research for EE[9,23], innovation capacity research for IC[33,34], and DC research for DC.[10,31] Item wording was contextualized to university startup activities. Construct scores were calculated as item means. The observed construct means (Ms) and standard deviations (SDs) were TI (M = 3.762, SD = 1.033), IC (M = 4.142, SD = 1.046), EE (M = 4.279, SD = 1.026), DC (M = 3.894, SD = 1.054), and I4R (M = 3.846, SD = 1.030). Observed maxima differ because of response patterns, not scale design.

No formal ethics committee approval was obtained for this survey, and no approval reference number exists. Participants received an electronic study information statement and provided informed consent before continuing. Participation was voluntary. Direct identifiers were removed, access to the working dataset was restricted to the research team, and findings are reported in aggregate.

Data provenance and analysis consistency were explicitly verified before final reporting. All PLS-SEM, bootstrapping, $PLS_{predict}$/CVPAT, ANN, and IPMA results reported in this article were generated from the same 250 case respondent dataset described above. The sampling frame for the empirical analysis comprised eligible participants from the three participating university-linked incubators under the stated inclusion criteria.

The model deliberately focuses on four proximal antecedents of I4R: TI, IC, EE, and DC. The model excludes institutional support, incubation services, funding access, mentorship quality, industry collaboration, market orientation, regulatory support, and startup maturity. Their omission means that the coefficients should be interpreted as unique associations within the specified model rather than as an exhaustive explanation of readiness. **Table 3** reports the descriptive statistics for the construct scores and their measurement indicators.

3.3. Common method bias assessment

Common method bias was assessed using Harman's single-factor test and full-collinearity variance inflation factor (VIF) diagnostics. The single factor accounted for 42.335% of variance, below the conventional 50% reference point, and construct VIF values ranged from 1.120 to 2.309, below 3.3.[35,36] Procedural remedies included anonymity, separated predictor and outcome item blocks, and instructions that there were no right or wrong answers. These checks reduce

Table 3. Descriptive statistics of construct and item-level indicators ($n = 250$)

Variable	*N*	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
TI (Construct)	250	1.00	6.40	3.762	1.033	−0.130	−0.343
IC (Construct)	250	1.40	6.60	4.142	1.046	−0.032	−0.420
EE (Construct)	250	1.20	7.00	4.279	1.026	−0.011	−0.190
DC (Construct)	250	1.00	6.40	3.894	1.054	−0.246	−0.327
I4R (Construct)	250	1.00	6.40	3.846	1.030	−0.166	−0.370
TI1	250	1	6	3.756	1.158	−0.012	−0.441
TI2	250	1	7	3.784	1.179	−0.003	−0.213
TI3	250	1	7	3.764	1.167	−0.249	−0.129
TI4	250	1	7	3.748	1.160	−0.274	−0.266
TI5	250	1	7	3.760	1.168	−0.071	−0.080
IC1	250	1	7	4.140	1.186	0.061	−0.340
IC2	250	1	7	4.124	1.191	0.017	−0.466
IC3	250	1	7	4.136	1.167	−0.130	−0.038
IC4	250	1	7	4.148	1.161	−0.137	−0.172
IC5	250	1	7	4.160	1.185	−0.021	−0.341
EE1	250	1	7	4.292	1.154	−0.099	−0.148
EE2	250	1	7	4.304	1.194	0.065	−0.384
EE3	250	2	7	4.240	1.161	0.127	−0.359
EE4	250	1	7	4.288	1.171	−0.017	−0.158
EE5	250	1	7	4.272	1.181	−0.144	0.001
DC1	250	1	6	3.876	1.150	−0.075	−0.775
DC2	250	1	7	3.908	1.170	−0.093	0.019
DC3	250	1	6	3.884	1.195	−0.159	−0.424
DC4	250	1	7	3.900	1.203	−0.141	−0.012
DC5	250	1	7	3.900	1.220	−0.195	−0.376
I4R1	250	1	7	3.856	1.142	−0.122	0.009
I4R2	250	1	7	3.848	1.165	−0.007	−0.398
I4R3	250	1	7	3.840	1.208	−0.253	−0.136
I4R4	250	1	7	3.840	1.185	−0.022	−0.490
I4R5	250	1	7	3.844	1.163	−0.124	−0.072

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

concern but do not prove the absence of common method bias; no marker-variable or longitudinal separation test was available. **Table 4** reports the common method bias diagnostics.

Figure 2 summarizes the Harman single-factor and full-collinearity VIF diagnostics.

3.4. Measurement model

Measurement quality was evaluated using outer loadings, Cronbach's alpha, rho_A, composite reliability (CR), average variance extracted (AVE), and heterotrait–monotrait (HTMT) ratios.[28,37] All loadings exceeded 0.70, AVE exceeded 0.50, and HTMT values were below 0.85. Alpha and CR values above 0.90 indicate strong internal consistency, but values this high can also indicate closely overlapping item content. **Figure 3** displays the reliability and convergent-validity results for the five constructs.

Table 5 reports Cronbach's alpha, rho_A, CR, and AVE for each construct.

Table 6 presents the outer loadings of all reflective measurement indicators.

Table 7 reports the HTMT ratios used to assess discriminant validity.

Table 8 presents the inner model variance inflation factors used to assess collinearity.

3.5. Analytical procedure

Partial least squares-SEM was used for measurement and structural model estimation, ANN for complementary predictive ranking, and IPMA for intervention prioritization.[16,28] PLS-SEM was estimated in SmartPLS 4.1.1.8 using path weighting, standardized results, a maximum of 3,000 iterations, and a stopping criterion of 10^{-7}. The dataset contained no missing observations. Statistical significance was assessed using 5,000 nonparametric bootstrap resamples, two-tailed tests at the 5% level, and percentile-bootstrap 95% confidence intervals (CIs). The structural assessment reported path coefficients, R^2, adjusted R^2, f^2, collinearity VIF, reliability, convergent validity, and discriminant validity. Because the design is cross-sectional, path estimates are interpreted as theory-consistent associations rather than causal effects.

For out-of-sample assessment, $PLS_{predict}$ and CVPAT used 10 folds, 10 repetitions, early antecedent prediction, path weighting, standardized results, and a fixed seed.[17,38,39] $Q^2_{predict}$, root mean square error (RMSE), and mean absolute error (MAE) were evaluated against linear-model and indicator-average benchmarks. For ANN analysis, SmartPLS latent-variable scores for DC, EE, IC, and TI were used as inputs and I4R as the continuous outcome. The ANN was implemented in Python 3 using scikit-learn 1.8.0 (MLPRegressor). Predictors and the outcome were standardized within each training fold to avoid information leakage. A single-hidden-layer multilayer perceptron used tanh hidden activation, an identity output, Adam optimization, L2 regularization (alpha = 0.001), initial learning rate = 0.001, and early stopping. Hidden-layer sizes from 1 to 10 were screened using repeated 10-fold cross-validation (3 repetitions); the retained four-input model used seven hidden

Table 4. Common method bias diagnostics

Test	Results	Threshold	Decision
Harman single-factor variance	42.335%	<50%	Single-factor dominance not indicated; interpret cautiously
Full collinearity VIF: TI	1.611	<3.3	Below 3.3; no problematic full-collinearity signal
Full collinearity VIF: IC	1.120	<3.3	Below 3.3; no problematic full-collinearity signal
Full collinearity VIF: EE	1.420	<3.3	Below 3.3; no problematic full-collinearity signal
Full collinearity VIF: DC	2.309	<3.3	Below 3.3; no problematic full-collinearity signal
Full collinearity VIF: I4R	2.150	<3.3	Below 3.3; no problematic full-collinearity signal

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure; VIF: Variance inflation factor.

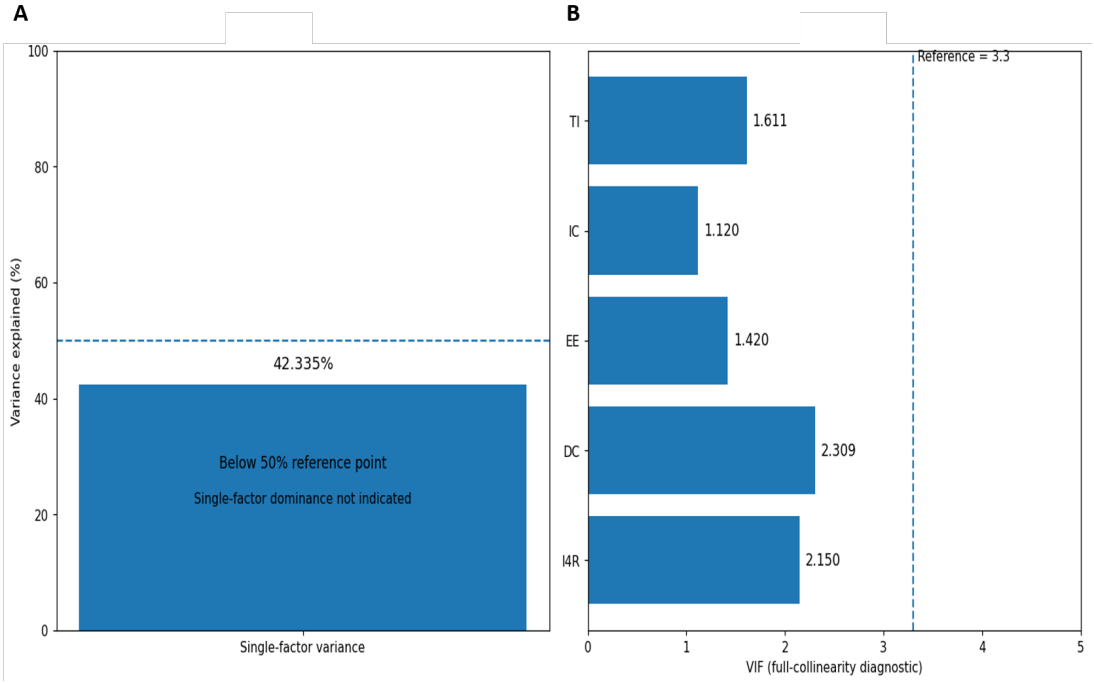


Figure 2. Common method bias diagnostics. (A) Harman's single-factor test and (B) full-collinearity VIF assessment.
Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure; VIF: Variance inflation factor.

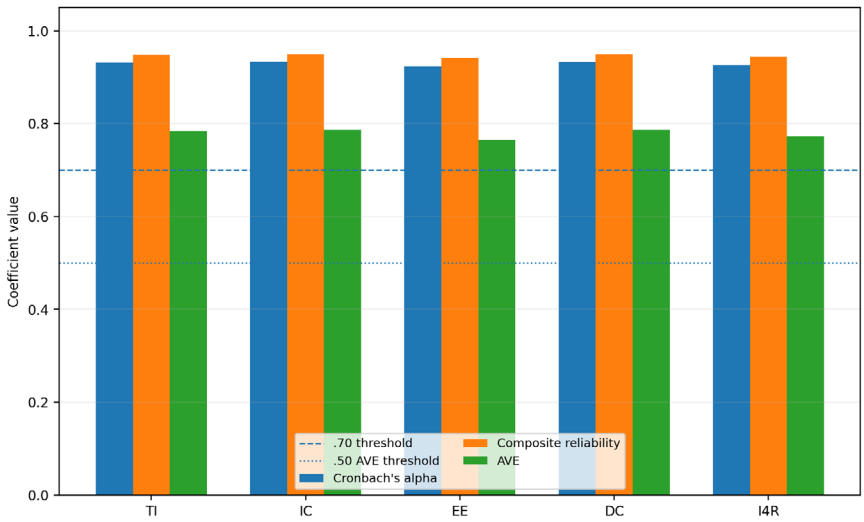


Figure 3. Reliability and convergent validity: All constructs
Notes: Blue = Cronbach's alpha; green = composite reliability; orange = average variance extracted (AVE); dashed red line = 0.70 threshold; dotted purple line = 0.50 AVE threshold. All criteria were satisfied.

neurons and was then evaluated using 10-fold cross-validation repeated 10 times (100 held-out folds). The maximum training iterations were 2,000; the early-stopping validation fraction was 0.10; n iter no change was 30; and tol was 1e−4. Reproducibility used a base random seed of 20,260,903, with fold-specific random states generated as the base seed plus the fold index. Predictor importance was estimated by held-out permutation sensitivity and normalized to the largest mean RMSE increase. IPMA targeted I4R using direct predecessors, path weighting,

Table 5. Reliability and convergent validity

Construct	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted	Decision
TI	0.931	0.932	0.948	0.784	Accept
IC	0.933	0.965	0.949	0.787	Accept
EE	0.923	0.924	0.942	0.765	Accept
DC	0.932	0.933	0.949	0.787	Accept
I4R	0.926	0.926	0.944	0.772	Accept

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

Table 6. Outer loadings of all reflective indicators

Construct	Indicator	Outer loading	Decision
TI	TI1	0.897	Accept (>0.70)
TI	TI2	0.873	Accept (>0.70)
TI	TI3	0.899	Accept (>0.70)
TI	TI4	0.872	Accept (>0.70)
TI	TI5	0.886	Accept (>0.70)
IC	IC1	0.906	Accept (>0.70)
IC	IC2	0.872	Accept (>0.70)
IC	IC3	0.879	Accept (>0.70)
IC	IC4	0.891	Accept (>0.70)
IC	IC5	0.887	Accept (>0.70)
EE	EE1	0.886	Accept (>0.70)
EE	EE2	0.883	Accept (>0.70)
EE	EE3	0.859	Accept (>0.70)
EE	EE4	0.870	Accept (>0.70)
EE	EE5	0.876	Accept (>0.70)
DC	DC1	0.883	Accept (>0.70)
DC	DC2	0.877	Accept (>0.70)
DC	DC3	0.892	Accept (>0.70)
DC	DC4	0.880	Accept (>0.70)
DC	DC5	0.904	Accept (>0.70)
I4R	I4R1	0.894	Accept (>0.70)
I4R	I4R2	0.874	Accept (>0.70)
I4R	I4R3	0.868	Accept (>0.70)
I4R	I4R4	0.881	Accept (>0.70)
I4R	I4R5	0.876	Accept (>0.70)

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

Table 7. Heterotrait–monotrait discriminant validity matrix

Construct	TI	IC	EE	DC	I4R
TI	1.000	–	–	–	–
IC	0.220	1.000	–	–	–
EE	0.347	0.299	1.000	–	–
DC	0.609	0.272	0.551	1.000	–
I4R	0.608	0.293	0.480	0.743	1.000

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

Table 8. Structural model collinearity for Industry 4.0 readiness

Endogenous	Predictor	VIF	Decision
I4R	DC	1.808	Ok
I4R	EE	1.399	Ok
I4R	IC	1.112	Ok
I4R	TI	1.487	Ok

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure; VIF: Variance inflation factor.

standardized results, and the theoretical 1–7 indicator scale for 0–100 performance rescaling.[18]

4. Results

4.1. Structural path analysis

The structural path estimates are visualized in **Figure 4** and summarized in **Table 9**. Nonparametric bootstrapping with 5,000 resamples was used to obtain statistics and 95% percentile-bootstrap CIs.[28] Because the data are cross-sectional, the coefficients are interpreted as associations rather than causal effects. **Figure 4** presents the final direct path coefficients and 95% percentile-bootstrap CIs corresponding to **Table 9**.

Hypothesis 1 (TI→I4R) was supported. TI was positively associated with I4R ($\beta = 0.241$, $t = 4.518$, $p < 0.001$, 95% percentile CI: 0.134, 0.345; $f^2 = 0.084$). The effect size is small, indicating that TI contributes meaningful but incremental explanatory value beyond the other predictors.

Hypothesis 2 (IC→I4R) was not supported. The IC–I4R association was positive but not statistically significant ($\beta = 0.083$, $t = 1.681$, $p = 0.093$, 95% percentile CI: −0.011, 0.182; $f^2 = 0.013$). The CI includes zero, and the incremental effect size is negligible.

Hypothesis 3 (EE→I4R) was supported at the 5% level, but the effect was small and borderline ($\beta = 0.095$, $t = 1.987$, $p = 0.047$, 95% percentile CI: 0.002, 0.192; $f^2 = 0.014$). The result should therefore be interpreted as a weak positive association rather than a strong or robust readiness effect.

Hypothesis 4 (DC→I4R) was supported. DC had the largest association with I4R ($\beta = 0.485$, $t = 8.239$, $p < 0.001$, 95% percentile CI: 0.367, 0.597; $f^2 = 0.282$). This medium effect identifies DC as the dominant explanatory predictor in the direct effects model.

Collectively, DC, TI, EE, and IC explained 53.8% of the variance in I4R ($R^2 = 0.538$; adjusted $R^2 = 0.530$). The relative effect-size pattern was DC (0.282) > TI (0.084) > EE (0.014) > IC (0.013), indicating that the model's explanatory contribution is concentrated primarily in DC and, to a lesser extent, TI. **Table 9** summarizes the structural-model coefficients, significance tests, effect sizes, and explained variance.

Figure 5 consolidates the principal structural-model results, including path coefficients, effect sizes, explained variance, and construct-level predictive relevance.

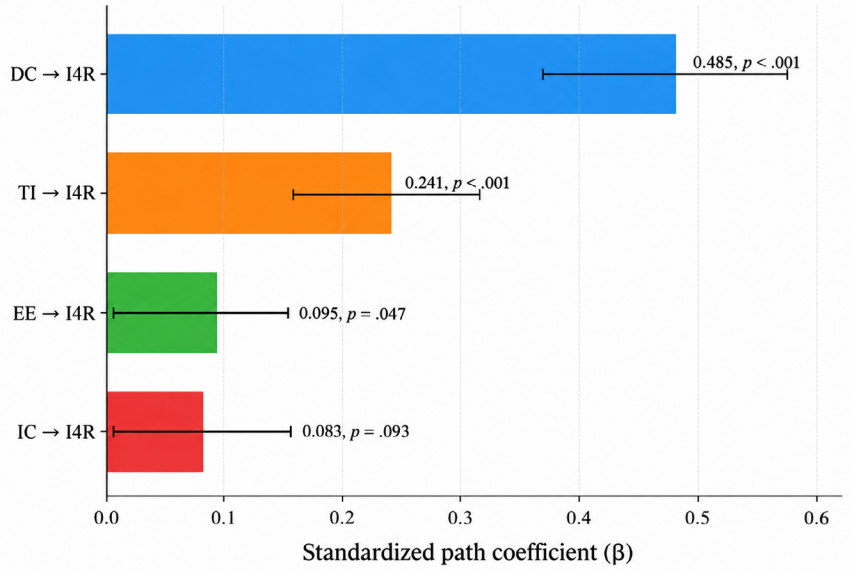


Figure 4. Structural path coefficients with 95% percentile-bootstrap confidence intervals
Notes: DC and TI are significant at $p < 0.001$; EE is marginally significant at $p = 0.047$; IC is not significant at $p = 0.093$.
Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

Table 9. Structural model summary

Hypothesis	Path	β	*t*-value	*p*-value	95% percentile CI	f^2	Decision
H1	TI→I4R	0.241	4.518	<0.001	0.134, 0.345	0.084	Supported
H2	IC→I4R	0.083	1.681	0.093	−0.011, 0.182	0.013	Not supported
H3	EE→I4R	0.095	1.987	0.047	0.002, 0.192	0.014	Supported (marginal)
H4	DC→I4R	0.485	8.239	<0.001	0.367, 0.597	0.282	Supported
Model	$R^2 = 0.538$				Adj. $R^2 = 0.530$		Moderate explanatory power

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

4.2. Artificial neural network model specification and predictive performance

The preferred ANN used all four theoretically specified predictors (DC, EE, IC, and TI) as latent-variable inputs and I4R as a continuous output. A feedforward multilayer perceptron with one hidden layer was used. Hidden layer sizes from one to ten neurons were screened using repeated 10-fold cross-validation (three repetitions), and the seven-neuron architecture produced the lowest mean test RMSE among the tested configurations. The selected architecture was then evaluated using 10-fold cross-validation repeated ten times.

Across 10 repetitions of 10-fold cross-validation, the retained ANN produced a mean training RMSE of 0.707, mean testing RMSE of 0.713, mean testing MAE of 0.561, and mean testing R^2 of 0.444. Training and testing errors were similar, providing no indication of major

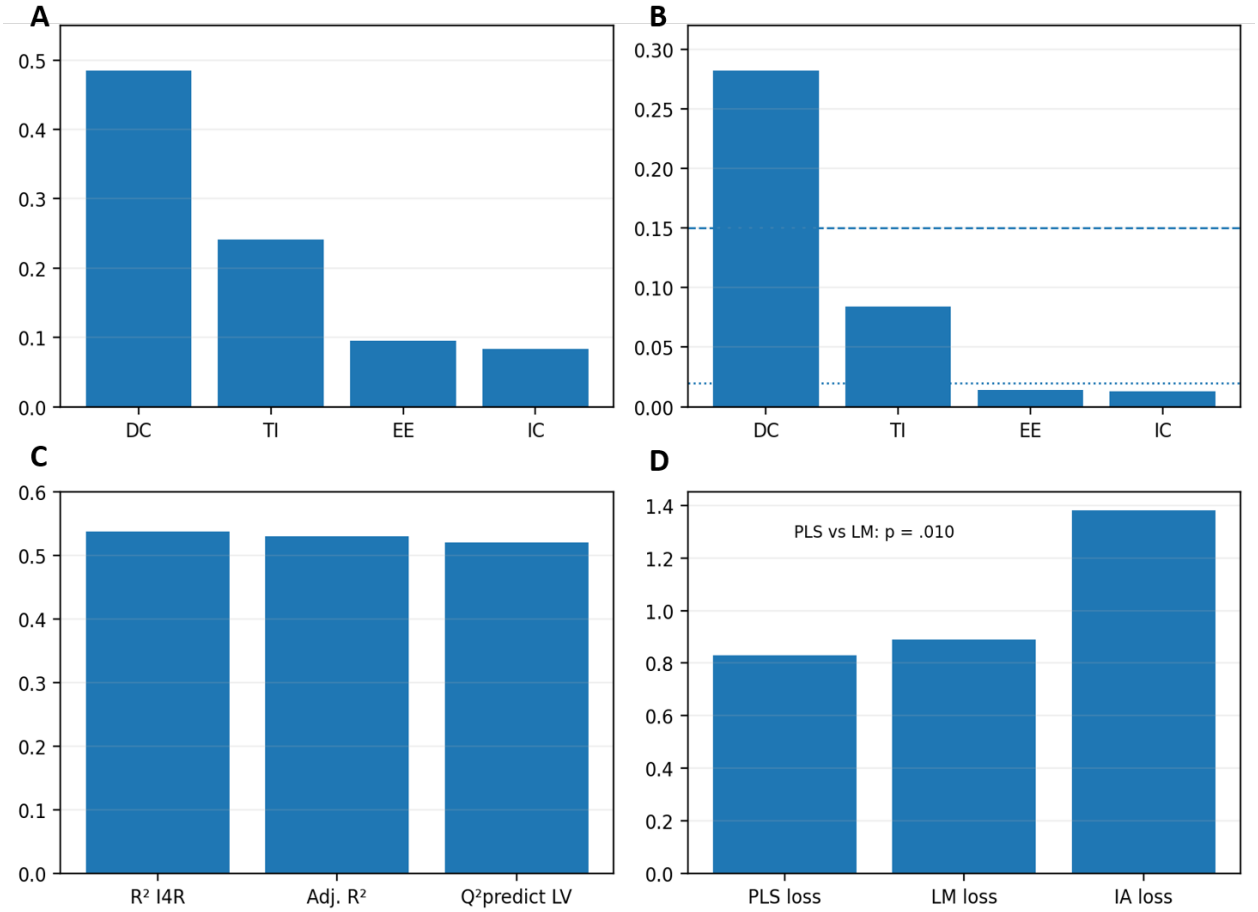


Figure 5. Integrated partial least squares (PLS) structural equation modeling structural and predictive summary for Industry 4.0 readiness. (A) Path coefficients. (B) Effect sizes. (C) Explanatory/predictive relevance. (D) Cross-validated predictive ability test construct-level loss.
Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

overfitting in the repeated held-out evaluations. The predictive results remain non-causal and should be interpreted as complementary to the PLS-SEM findings.

A matched multiple linear regression benchmark evaluated on the identical held-out folds achieved lower mean RMSE (0.686) and MAE (0.537), with mean $R^2 = 0.481$. Accordingly, the ANN results do not support a claim of superior out-of-sample predictive accuracy over the linear benchmark. The ANN is retained as a complementary nonlinear sensitivity and predictor-ranking analysis. **Table 10** summarizes the retained ANN specification, validation design, and predictive performance.

Figure 6 compares ANN and linear-benchmark RMSE across the repeated cross-validation runs.

4.3. Artificial neural network sensitivity and predictor importance

Held-out permutation sensitivity was used to quantify each predictor's contribution to ANN prediction. Importance was defined as the mean increase in test RMSE after permuting a predictor within each held-out fold and was normalized relative to the largest mean increase. DC ranked first with 100% normalized importance, followed by TI (47.6%), EE (10.9%), and IC (10.0%).

The ANN ranking should not be interpreted as a causal coefficient or as evidence of nonlinear thresholds. Its role is to provide complementary predictive importance. The linear benchmark's lower held-out RMSE further supports a restrained interpretation of ANN as a ranking and sensitivity tool rather than a superior

Table 10. Artificial neural network model specification and repeated cross-validation performance

Element	Final specification/result
Inputs	DC, EE, IC, and TI latent-variable scores
Outcome	I4R latent-variable score
Architecture	4 inputs → 7 hidden neurons → 1 output; one hidden layer
Activation	Tanh hidden; identity/linear output
Optimization	Adam; L2 regularization $\alpha = 0.001$; learning rate = 0.001
Validation	Architecture screening: repeated 10-fold CV ×3; final evaluation: 10-fold CV ×10 (100 held-out folds)
Mean training RMSE	0.707
Mean testing RMSE/MAE	0.713/0.561
Mean testing R^2	0.444
Linear benchmark	RMSE = 0.686; MAE = 0.537; $R^2 = 0.481$
Software/version	Python 3; scikit-learn 1.8.0 MLPRegressor
Training/stopping	max_iter = 2,000; early stopping; validation fraction = 0.10; patience = 30; tol = 1e−4
Preprocessing	Predictors and I4R standardized within each training fold; predictions inverse-transformed for metrics
Reproducibility seed	Base seed 20,260,903; fold-specific random state = base seed + fold index

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; MAE: Mean absolute error; RMSE: Root mean square error; TI: Technological infrastructure.

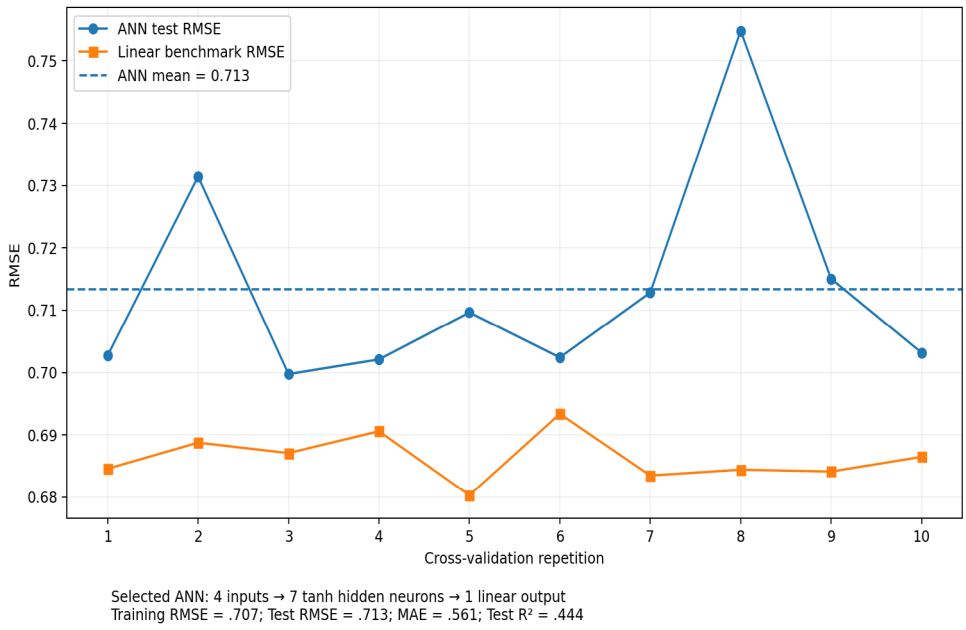


Figure 6. Repeated 10-fold cross-validation: Artificial neural network (ANN) versus linear benchmark
Abbreviation: RMSE: Root mean square error.

forecasting model.

The ANN ranking, DC > TI > EE > IC, is consistent with the ordering of the PLS-SEM direct coefficients. This qualitative convergence strengthens the identification of DC and TI as the two most consequential predictors in the model, while the low ANN importance of IC is consistent with its nonsignificant PLS-SEM direct path. Numerical ANN importance percentages and PLS-SEM coefficients remain on different scales and are not compared as equivalent effect sizes. **Table 11** compares ANN normalized importance with the corresponding PLS-SEM direct associations.

Figure 7 provides a visual comparison of ANN normalized importance and PLS-SEM direct associations across the four predictors.

4.4. Importance–performance map analysis

The IPMA targeted I4R and mapped each direct predecessor's total effect (importance) against its performance rescaled to 0–100 using the theoretical 1–7 indicator ranges. Because all four predecessors enter I4R directly, constructing importance corresponds to their total direct effect in this specification. The corrected scale settings ensure that observed response minima and maxima do not distort performance scores. **Figure 8** maps construct importance against performance for the I4R target.

The IPMA identified DC (importance = 0.485; performance = 48.222) as the leading intervention priority, followed by TI (0.241; 46.037). EE had lower importance (0.095) but the highest performance (54.659), while IC showed the lowest importance (0.083) and moderate performance (52.380). The construct-level priority order is therefore DC > TI > EE > IC. **Table 12** reports the construct-level importance and performance values used to interpret the IPMA map.

4.5. Indicator-level importance–performance map analysis priorities

Indicator-level IPMA was used to identify specific operational priorities within the four constructs. The DC indicators had the highest importance values overall, led by DC1 (0.115), DC5 (0.113), and DC2 (0.109), while their performance scores remained around 48. Among TI indicators, importance ranged from 0.053 to 0.056, and performance ranged from 45.800 to 46.400.

The strongest indicator-level improvement opportunities therefore lie within DC first and TI second. Within DC, DC1 combines the highest importance with relatively low performance; DC5 and DC2 follow closely. Within TI, TI3 has the highest importance (0.056), while TI4 has the lowest performance (45.800). EE and IC indicators show substantially lower importance and are secondary priorities within this model. **Table 13** reports the indicator-level importance and performance values for the DC/TI priority indicators alongside the lower-priority EE/IC indicators.

The indicator-level results reinforce the construct-level conclusion: managerial attention should first focus on digital-capability items, then on technological-infrastructure items. These rankings are relative priorities within the current

Table 11. Artificial neural network sensitivity ranking and partial least squares structural equation modeling associations

Predictor	ANN normalized importance	PLS-SEM direct association	Complementary interpretation
DC	100.0%	$\beta = 0.485$, $p < 0.001$	Rank 1 in ANN; strongest PLS-SEM path
TI	47.6%	$\beta = 0.241$, $p < 0.001$	Rank 2 in ANN; significant PLS-SEM path
EE	10.9%	$\beta = 0.095$, $p = 0.047$	Low ANN importance; marginal PLS-SEM path
IC	10.0%	$\beta = 0.083$, $p = 0.093$	Lowest ANN importance; PLS-SEM path not significant

Abbreviations: ANN: Artificial neural network; DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; MAE: Mean absolute error; PLS-SEM: Partial least squares structural equation modeling; RMSE: Root mean square error; TI: Technological infrastructure.

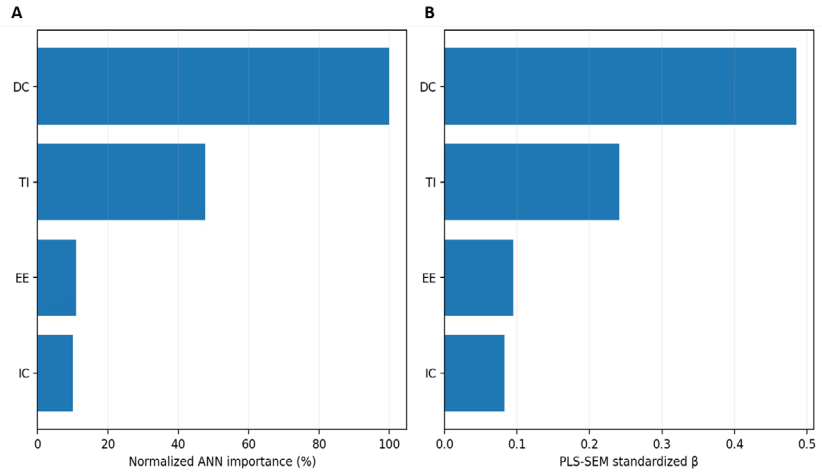


Figure 7. Complementary predictor ranking: (A) artificial neural network (ANN) normalized importance and (B) partial least squares structural equation modeling (PLS-SEM) direct associations
Note: ANN normalized importance and standardized PLS-SEM coefficients quantify different aspects of the model and are shown as complementary, not numerically equivalent, evidence.
Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

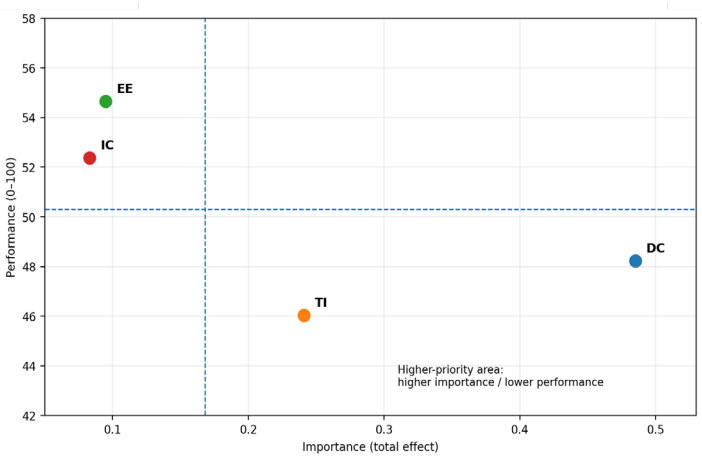


Figure 8. Importance–performance map targeting Industry 4.0 readiness
Note: X-axis = importance (total effect); Y-axis = performance on the 0–100 scale. Higher importance combined with lower performance indicates a stronger improvement opportunity.
Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

sample and do not imply that improving an item will causally produce a proportional change in I4R.

4.6. Scenario-based sensitivity analysis of importance–performance map analysis priorities

To assess whether the managerial priority conclusion depended on the relative emphasis placed on construct importance versus performance gaps, a decision-weight sensitivity analysis was conducted using the final IPMA values. Importance was normalized to the largest construct importance (0.485), while the performance gap was defined as 100 minus the performance score and normalized to the largest observed gap (53.963). Composite priority scores were then calculated under three prespecified importance-to-gap weighting scenarios: 25:75, 50:50, and 75:25. This exercise evaluates decision-priority stability; it is not a sensitivity test of

Table 12. Construct-level importance–performance map analysis targeting Industry 4.0 readiness

Construct	Importance	Performance (0–100)	Priority	Interpretation
DC	0.485	48.222	1	Highest importance with moderate performance
TI	0.241	46.037	2	Second-highest importance and lowest performance
EE	0.095	54.659	3	Low importance; highest performance
IC	0.083	52.380	4	Lowest importance; moderate performance

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

Table 13. Indicator-level importance–performance map analysis: Importance and performance

Priority indicator	Importance	Performance	Rank	Other indicator	Importance	Performance
DC1	0.115	47.933	1	EE1	0.023	54.867
DC5	0.113	48.333	2	EE2	0.022	55.067
DC2	0.109	48.467	3	EE3	0.021	54.000
DC3	0.105	48.067	4	EE4	0.022	54.800
DC4	0.105	48.333	5	EE5	0.022	54.533
TI3	0.056	46.067	6	IC1	0.025	52.333
TI5	0.055	46.000	7	IC2	0.014	52.067
TI4	0.054	45.800	8	IC3	0.015	52.267
TI1	0.054	45.933	9	IC4	0.019	52.467
TI2	0.053	46.400	10	IC5	0.020	52.667

Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; TI: Technological infrastructure.

the estimated PLS-SEM coefficients or ANN predictions.

Under the performance-gap-dominant 25:75 scenario, the composite scores were DC = 0.970, TI = 0.874, IC = 0.705, and EE = 0.679 (DC > TI > IC > EE). Under balanced 50:50 weighting, the scores were DC = 0.980, TI = 0.748, IC = 0.527, and EE = 0.518 (DC > TI > IC > EE). Under importance-dominant 75:25 weighting, the scores were DC = 0.990, TI = 0.623, EE = 0.357, and IC = 0.349 (DC > TI > EE > IC). Thus, DC and TI remained the top two priorities in every scenario, while only the ordering of the two lower-priority constructs changed.

4.7. Out-of-sample predictive assessment: Partial least squares$_{\text{predict}}$ and cross-validated predictive ability test

Partial least squares$_{\text{predict}}$ produced positive Q^2_{predict} values for all five I4R indicators, ranging from 0.369 to 0.417. The construct-level Q^2_{predict} value was 0.520 (RMSE = 0.700; MAE = 0.542). PLS-SEM also produced lower RMSE values than the linear-model benchmark for all five I4R indicators, demonstrating consistent out-of-sample predictive improvement.

The cross-validated predictive ability test provided a formal benchmark test. At the manifest-variable level, PLS-SEM prediction loss

was significantly lower than the indicator-average benchmark for all five indicators (all $p < 0.001$). Compared with the more demanding linear-model benchmark, PLS-SEM loss was lower for all indicators, although indicator-level differences were significant only for I4R2 ($p = 0.041$) and I4R5 ($p < 0.001$). At the latent-variable level, PLS-SEM achieved significantly lower overall prediction loss than the linear model (PLS loss = 0.831; LM loss = 0.890; average loss difference = −0.059; $t = 2.602$; $p = 0.010$). Thus, the construct-level result supports superior predictive ability relative to the linear benchmark, while the indicator-level evidence remains heterogeneous. **Table 14** reports the $PLS_{predict}$ results for the five I4R indicators.

5. Discussion

5.1. Structural associations and explanatory power

The direct-effects model identifies DC as the dominant correlate of I4R (β = 0.485; f^2 = 0.282), followed by TI (β = 0.241; f^2 = 0.084). Together with EE and IC, the four predictors explain 53.8% of the variance in readiness. The magnitude of the DC coefficient is consistent with the view that access to technology is insufficient unless startup teams can deploy digital resources for value creation, operational improvement, and innovation.[10,31] Because the design is cross-sectional, this result supports association rather than temporal causation.

Technological infrastructure's significant association with I4R supports the practical relevance of cloud services, IoT test beds, data platforms, AI-enabled tools, and reliable digital infrastructure in university startup environments.[7,8,24] EE showed a much smaller, borderline association (β = 0.095, $p = 0.047$; f^2 = 0.014). This suggests that EE may contribute to readiness, but its unique direct contribution is limited once DC, TI, and IC are considered simultaneously.

5.2. Interpretation of the nonsignificant innovation capacity association

Innovation capacity was not significantly associated with I4R in the final direct-effects model (β = 0.083, $p = 0.093$; f^2 = 0.013). This result indicates limited unique explanatory contribution from IC after DC, TI, and EE are included. It does not establish that IC is ineffective or irrelevant in university startup ecosystems.

One possible explanation is resource complementarity. Innovative ideas may be difficult to translate into I4R when practical DC, infrastructure access, or relevant entrepreneurial learning is limited.[12,33,34] This interpretation is theoretically plausible, but it was not directly tested and should therefore be treated as a proposition for future research.

A second explanation concerns construct scope. IC captures ideation, experimentation, and knowledge combination, whereas I4R captures broader preparedness to access, combine, and deploy Industry 4.0 technologies. The concepts are related but not equivalent, which may partly explain the weak unique coefficient for IC once DC, TI, and EE are included.

Shared variance among DC, TI, EE, and IC may also reduce each predictor's unique

Table 14. Partial least $squares_{predict}$ results for Industry 4.0 readiness indicators

Indicator	$Q^2_{predict}$	PLS-SEM RMSE	LM RMSE	PLS-SEM MAE	LM MAE
I4R1	0.417	0.875	0.897	0.684	0.713
I4R2	0.369	0.928	0.965	0.752	0.789
I4R3	0.411	0.930	0.960	0.725	0.755
I4R4	0.392	0.926	0.942	0.730	0.747
I4R5	0.407	0.897	0.950	0.719	0.766

Note: $PLS_{predict}$ used 10 folds, 10 repetitions, early antecedent prediction, path weighting, standardized results, and a fixed seed.
Abbreviations: DC: Digital capability; EE: Entrepreneurship education; I4R: Industry 4.0 readiness; IC: Innovation capacity; LM: Linear-model benchmark; TI: Technological infrastructure.

coefficient. The structural VIF values are low and rule out severe collinearity, but they do not establish a suppression or dominance mechanism. No formal dominance analysis was conducted, so such mechanisms are not claimed.

Moderation remains another possible explanation. The association between IC and I4R may differ across levels of TI, DC, funding, mentorship, or startup maturity. Because no interaction terms were estimated, the present study cannot label IC as boundary-conditioned. Future work should directly test theoretically justified interactions and conditional effects.

The nonsignificant IC result refines the model by separating innovation potential from readiness to deploy Industry 4.0 technologies. Institutions should therefore avoid assuming that ideation and experimentation alone are sufficient for digital readiness. Future research can test whether IC becomes more consequential under different infrastructure, funding, mentorship, or startup-maturity conditions.

5.3. Predictive and priority evidence from partial least squares$_{\text{predict}}$, artificial neural network, and importance–performance map analysis

The fully specified repeated-cross-validated ANN ranking places DC first and TI second, followed by EE and IC. The normalized importance values were 100%, 47.6%, 10.9%, and 10.0%, respectively. This ordering is consistent with the PLS-SEM coefficient ranking, but the methods measure different quantities. ANN sensitivity reflects predictive contribution under permutation, whereas PLS-SEM coefficients represent standardized linear associations. The matched linear benchmark achieved lower held-out ANN RMSE, so the ANN evidence should be treated as complementary ranking rather than proof of superior nonlinear prediction.

Importance–performance map analysis translates the direct effects into a decision-oriented comparison by adding performance. DC combines the highest importance (0.485) with moderate performance (48.222), while TI combines the second-highest importance (0.241) with the lowest construct performance (46.037). These results identify DC and TI as the top priorities for improvement. Indicator-level IPMA further highlights DC1, DC5, and DC2, followed by TI3, TI5, TI4, TI1, and TI2.

Partial least squares$_{\text{predict}}$ and CVPAT provide a distinct out-of-sample assessment. Positive Q^2_{predict} values and lower PLS-SEM RMSE than the linear benchmark across all five I4R indicators support predictive relevance. The construct-level CVPAT result is significantly better than the linear benchmark, although only two indicator-level comparisons reach significance. This combination supports a measured claim of predictive usefulness rather than universal superiority at every indicator.

5.4. Most important consequences for university ecosystem governance

The main governance implication is that intervention sequencing should reflect both importance and performance. The evidence consistently places DC first and TI second across PLS-SEM, ANN ranking, and IPMA. The scenario-based decision-weight sensitivity analysis also retained DC and TI as the top two priorities under performance-gap-dominant, balanced, and importance-dominant weighting. Universities and incubators should therefore prioritize practical digital deployment capability and shared TI before allocating additional resources to lower-importance readiness dimensions, while continuing to maintain EE and IC.

Entrepreneurship education can be redesigned as an applied capability-building mechanism connecting venture problems with data analytics, AI, IoT, cloud tools, prototyping, market validation, and partnership breaking.[21,26] Incubators can track TI, DC, EE, and IC scores as a diagnostic dashboard, while startup teams can use the same profile to identify immediate skill, platform, and mentoring needs. The dashboard should support discussion and resource allocation, not replace managerial judgment.

6. Conclusion

6.1. Theoretical contributions

This study evaluated an integrated quantitative framework combining PLS-SEM, PLS$_{\text{predict}}$/CVPAT, ANN, and IPMA using 250 survey responses from a university startup ecosystem context. PLS-SEM showed that DC had the strongest association with I4R, followed by TI; EE showed a small marginal association, while IC was not significant. The model explained 53.8% of the variance in I4R. The integrated approach uses quantitative methods throughout. PLSpredict and CVPAT strengthen the assessment by demonstrating out-of-sample predictive relevance for the PLS-SEM

component. All five I4R indicators had positive Q^2_{predict} values, PLS-SEM RMSE was lower than the linear model benchmark for all five indicators, and construct-level CVPAT showed significantly lower prediction loss than the linear benchmark.

Innovation capacity was not significantly associated with I4R in the final direct-effects model ($\beta = 0.083$, $p = 0.093$; $f^2 = 0.013$). This result indicates limited unique explanatory contribution from IC after DC, TI, and EE are included. It does not establish that IC is ineffective or irrelevant in university startup ecosystems.

6.2. Practical implications

The findings support a staged but locally adaptable improvement agenda. Universities can strengthen practical DC through access to data analytics, cloud services, AI-enabled tools, digital prototyping, and platform-based venture development. At the same time, institutions should address shared infrastructure constraints reflected in TI's low performance. EE should be maintained and digitally refocused, while IC should remain supported without being treated as the highest-priority readiness lever in this sample.

- Universities: Assess shared infrastructure gaps first and prioritize cloud, IoT, data, and AI-platform access where TI performance is low.
- Incubators and educators: Embed data analytics, digital prototyping, technology commercialization, and intelligent-system literacy in venture-based learning.
- Policymakers: Support shared digital infrastructure, capability training, and outcome monitoring rather than standalone innovation events alone.
- Startup teams: Use the readiness profile to select one immediate capability gap, assign an owner, define a measurable 90-day action, and reassess progress.

6.3. Limitations

This study has several limitations. First, its cross-sectional design supports association but not temporal or causal ordering. Second, the criterion-based, non-probability sample from three Karachi incubators limits statistical generalization. Third, pooling four respondent roles may obscure differences in how respondents interpret the construct or in their structural associations. Measurement invariance, role-controlled estimation, and multigroup analysis were not conducted; the pooled coefficients cannot establish that the roles form a homogeneous population. The smallest role group represented 10% of the sample (approximately 25 respondents), which also limits the stability of four-group comparisons. Fourth, self-report data may retain common method bias despite procedural remedies, Harman's test, and full-collinearity VIF diagnostics; no marker variable or longitudinal method separation was available. Fifth, very high reliability values may indicate some item-content overlap and merit future content-based reassessment. Sixth, although ANN performance was evaluated using repeated 10-fold cross-validation with fully specified training settings[39], no independent external holdout sample was available, and the matched linear benchmark achieved lower held-out RMSE. Seventh, IPMA priorities are sample-relative and depend on the specified theoretical ranges; the scenario analysis tests the stability of managerial decision weights rather than the structural coefficients themselves. Finally, the model excluded institutional support, incubation services, funding access, mentorship quality, industry collaboration, market orientation, regulatory support, and startup maturity, which may affect the observed associations.

The multi-method components answer different questions and should not be conflated. PLS-SEM estimates explanatory associations, $\text{PLS}_{\text{predict}}$/CVPAT evaluates out-of-sample predictive ability, ANN provides sensitivity-based predictive ranking, and IPMA prioritizes constructs and indicators using importance and performance. The original mediation model has not been re-estimated on the same 250 responses; its indirect effects, I4R explained variance, and out-of-sample prediction remain to be compared with the revised specification.

6.4. Future research

Future research should use longitudinal, panel, or experimental designs to test whether changes in DC, TI, EE, and IC precede changes in I4R. Probability-based multi-institutional samples and cross-country comparisons would strengthen generalizability. Larger, more balanced role-specific samples would allow measurement invariance assessment, followed, where supported, by multigroup analysis of student entrepreneurs, venture representatives, faculty advisers, and innovation-center employees. Role-controlled estimates could provide an additional sensitivity check using a pooled model. External holdout

samples and nested model selection procedures can strengthen ANN validation. Partial-dependence or accumulated local effect plots can assess nonlinear patterns. Future work may also test theoretically justified mediated or moderated mechanisms using longitudinal evidence and established resampling procedures.[40,41]

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Conflict of interest

The authors declare no conflict of interest regarding the publication of this research.

Author contributions

Conceptualization: All authors
Formal analysis: Syed Rizwan Ali
Investigation: All authors
Methodology: Syed Rizwan Ali
Visualization: Syed Rizwan Ali
Writing – original draft: Syed Rizwan Ali
Writing – review & editing: All authors

Ethics approval and consent to participate

No formal ethics committee approval was obtained for this survey, and no approval reference number exists. All participants received an electronic study information statement and provided informed consent before accessing the questionnaire. Participation was voluntary. No direct identifiers were collected in the analytical dataset, access was restricted to the research team, and findings are reported only in aggregate form.

Availability of data

The respondent-level data is not publicly deposited because the participating incubators require confidentiality. The SmartPLS PLS-SEM, bootstrapping, PLSpredict/CVPAT outputs, and the fully specified ANN analysis code/settings, including the reproducibility seed, are retained with study records. Data supporting the findings of this study are available upon reasonable request to the corresponding author.

AI tools statement

Analytical visualizations were assisted using Python-based data analysis libraries (Plotly). All intellectual content, theoretical development, and interpretations were produced solely by the authors.

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Syed Rizwan Ali *received the B.S. degree in computer engineering from Sir Syed University of Engineering & Technology, Karachi, Pakistan, in 2004, a PGD in computing from London Academy of Management Sciences in 2005 and the M.S. degree in computer-aided design from the University of the West of England (UWE) Bristol, England, UK, in 2008. He is currently working as an Industry Consultant, Assistant Professor and Manager of the Business Incubation Center (BIC) at Bahria University, Karachi, Pakistan. His research interests include the development of innovative strategies for startups, entrepreneurship education, technology management, and technology commercialization, with a focus on integrating emerging technologies to enhance business scalability and industry impact. Judge Member at the Diamond Challenge through the Horn Entrepreneurship Center, University of Delaware, USA. He is an IVLP fellow on "Innovation and Incubation on U.S. Campuses: A Sub Regional Project" through the U.S. Department of State's Educational and Cultural Affairs. A certified Master Trainer for the Faculty Professional Development Program (FPDP) from the Higher Education Commission (HEC), Pakistan, for Level I, and Master Trainer for Good Governance Strategies for Organizational Excellence" at Tubitak,*

Tusside, Gebze, Turkey, for Level II. In the meantime, he has also performed the duties of a Regional Coordinator of Global Entrepreneurship Network (GEN) Pakistan, and Business Consultant for an improvement plan for SME's for the International Trade Center (ITC), United Nations (UN), European Union (EU), & Small Enterprise Medium Development Authority (SEMDA), Karachi, Sindh, Pakistan.
https://orcid.org/0000-0001-9976-0082

Muhammad Irfan *Memon is an Associate Professor and Programme Leader of the BEng (Hons) Electronics and Telecommunications Engineering programme in the Department of Electrical and Electronics Engineering at the Global College of Engineering and Technology (GCET), Muscat, Oman. He received his PhD in Electrical and Electronic Engineering from the University of Bristol, UK, in 2011. His research interests include optical fibre communications, photonics, semiconductor ring lasers, optical injection locking, nonlinear optical signal processing, wireless communications, and machine learning applications in smart energy systems. He has authored over 60 peer-reviewed publications and has contributed to several funded research projects and international collaborations. He is a Chartered Engineer (CEng) on the register of UK Engineering Council, a Member of the Institution of Engineering and Technology (MIET), and a Senior Member of the IEEE.*
https://orcid.org/0000-0003-3632-0092

Mohammad Mohatram *is an Associate Professor in the Department of Electrical and Electronics Engineering and Program Leader of the BEng (Hons) Instrumentation and Control Engineering (ICE) programme at the Global College of Engineering and Technology (GCET), Muscat, Oman, which delivers academic programmes in partnership with the University of the West of England (UWE), Bristol, UK. He received his Ph.D. in Electrical Engineering from Birla Institute of Technology (India) in 2014; an M.Tech. in Electrical Engineering, specializing in Instrumentation and Control, in 1999; a B.Sc. (Engineering) in Electrical Engineering in 1997; and a Diploma in Engineering in Electrical Instrumentation in 1993, all from Aligarh Muslim University (AMU), India. He also holds a Postgraduate Certificate in Academic Practices from UWE, UK. With over 25 years of experience in engineering education, research, and academic administration, he has published more than 50 research papers in journals and conference proceedings. His research interests include artificial neural networks, power systems, renewable energy, artificial intelligence, instrumentation and control, and Internet of Things (IoT) applications. He is a Chartered Engineer (CEng) with the Institution of Engineering and Technology (IET), a Senior Member of IEEE, and a Life Member of the Indian Society for Technical Education (ISTE). His professional activities include research supervision, peer review, and academic development.*
https://orcid.org/0000-0002-5459-5631

Muhammad Faraz *is currently working as a Senior Assistant Professor at Bahria University, Karachi, and has shown a dynamic presence in the field of management and business as a regular faculty member at multiple universities in Pakistan, with over 20 years of experience. He holds advanced degrees from Pakistan, including an MS in Supply Chain Management, an MSc in Industrial Psychology, and an MA in Media Studies. Faraz is currently pursuing his PhD in Supply Chain Management at a prominent Malaysian university. His professional journey includes significant roles such as an Ethical Standard Auditor and Consultant in Responsible Sourcing with companies like Walmart, Steve & Barry's, and CHF Industries USA, where he has worked for more than five years. Muhammad Faraz has contributed to over 19 publications in top-tier journals and has been recognized for his research prowess with a USAID research grant worth 12,000 USD.*
https://orcid.org/0000-0002-0403-2638

Muhammad Mumtaz Khan *is an Associate Professor in the Department of Business Studies at Bahria Business School, Bahria University Karachi Campus, Pakistan. He earned his Ph.D. in Management Sciences from Mohammad Ali Jinnah University, a Master's from SZABIST, Karachi, and his MBA in Finance from the Institute of Business Administration (IBA), Karachi. He also holds a degree in Textile Engineering from NED University of Engineering and Technology. His research interests include organizational behavior, leadership, human resource management, employee engagement, innovative work behavior, and intellectual capital. Dr. Khan has published extensively in international peer-reviewed journals, with notable contributions to servant leadership, employee innovation, and organizational performance. His research focuses on understanding leadership practices and employee behaviors that enhance organizational effectiveness and innovation.*
https://orcid.org/0000-0002-7365-6719

Javeed Hussain *works as the Head of the Department of Electronics and Telecommunication Engineering in the Global College of Engineering and Technology (GCET), Oman. He has a PhD degree in Electronics and Communication Engineering and has over 20 years of teaching experience. His research*

interests include artificial intelligence, deep learning, machine vision, medical image processing, feature optimization, embedded systems, and automation & robotics. His contributions to research include studies on the detection and classification of brain tumors, diagnosis of Alzheimer's disease, intelligent surveillance, and renewable energy monitoring. He is a Chartered Engineer (CEng), a Senior Member of IEEE, a Senior Fellow of the Higher Education Academy (SFHEA), and an IET member.
https://orcid.org/0000-0001-5300-189X

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