Smart and Sustainable Built Environment

Empirical validation of the next-gen digital project manager competency framework through exploratory factor analysis

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Abstract

Purpose – Digital transformation is reshaping project delivery in the construction sector, requiring Project Managers (PMs) to operate across increasingly complex technological, organisational, and sustainability-driven environments. Despite the growing importance of digital capabilities, there remains a lack of empirical evidence on the underlying structure of digital project management competencies in construction. This study aims to empirically validate the Next-Gen Digital PM Competency Framework for the construction sector.

Design/methodology/approach – Building on a previously developed and validated list of 55 digital PM competencies, survey data were collected from experienced construction professionals and analysed using Exploratory Factor Analysis (EFA). Principal Axis Factoring (PAF) with Promax rotation was employed to examine the latent structure of the competency set.

Findings – The results confirm a statistically robust seven-factor competency structure, supported by eigenvalue thresholds, scree plot interpretation, and thematic coherence. A total of 25 competencies were retained and grouped into seven latent constructs: Digital Execution and Optimisation; Human-Centred Digital Leadership; Lifecycle Risk and Compliance Knowledge; Digital Sustainability Intelligence; Digital Tools Proficiency and Automation; Digital Content and Data Management; and Digital Transformation Enablement Skills. Together, these factors capture the multidimensional nature of digital PM capability across technical, behavioural, and cognitive domains.

Originality/value – This study provides one of the first empirically validated digital project management competency frameworks tailored to digitally transformed construction environments. The findings demonstrate that digital PM competency extends beyond technical proficiency to encompass leadership, governance-related capabilities (e.g. lifecycle risk and compliance), sustainability, and transformation-oriented capabilities. The resulting framework offers an empirically grounded foundation for competency assessment, workforce development, and targeted professional upskilling in digitally enabled construction environments, while establishing a statistically validated basis for future confirmatory analysis.

Keywords Digital project management, Digital transformation, Competency framework, Exploratory factor analysis (EFA), Construction industry

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1. Introduction

The construction industry is undergoing a period of accelerated digital transformation, driven by the adoption of technologies such as Building Information Modelling (BIM), Digital Twins (DTs), the Internet of Things (IoT), smart sensors, and Artificial Intelligence (AI) (Vial, 2019; Liu *et al.*, 2022; Paneru *et al.*, 2024). These innovations are reshaping how projects are conceived, designed, and delivered by enabling real-time data exchange, predictive analytics, and lifecycle optimisation. However, prior research in Smart and Sustainable Built Environment highlights that digitally enabled delivery also depends on effective lifecycle information management, ensuring that the right data are delivered to the right actors at the right time and remain usable across the asset lifecycle, which has been identified as a continuing challenge in digital engineering and BIM-enabled environments (Hosseini *et al.*, 2021). As projects become increasingly interconnected and digitally mediated, the effectiveness of project management emerges as a decisive factor in harnessing these technologies to improve outcomes, reduce waste, and enable sustainable performance.

At the centre of this transformation is the project manager (PM), whose competencies directly influence project outcomes (Ahmed and Anantatmula, 2017). Competent PMs enhance delivery performance by coordinating multidisciplinary teams, mitigating risks, and aligning resources with strategic objectives. In digitally enabled contexts, their role extends beyond the traditional management of cost, time, and quality to that of digital integrators, collaboration facilitators, and data-driven decision enablers (Aibinu and Venkatesh, 2014; Whyte, 2019; Rodrigues *et al.*, 2023). Recent work published in Smart and Sustainable Built Environment demonstrates that DTs support lifecycle-oriented construction project management by enabling continuous monitoring, data-driven decision-making, and integrated oversight across BIM-enabled construction processes, particularly through services such as progress monitoring, communication and collaboration, scheduling, and risk management (Aktürk and Irlayıcı Çakmak, 2025). By aligning human, organisational, and technological dimensions, DTs make project management capability pivotal to realising value from digital transformation.

However, meeting these evolving expectations requires a new generation of PMs equipped with digital fluency, systems thinking, and adaptive leadership suited to technology-rich construction environments. Established project management competency frameworks, such as PMI's Talent Triangle (Project Management Institute, 2021) and IPMA's Individual Competence Baseline (ICB) (International Project Management Association IPMA, 2015), were primarily developed to support general project management practice and do not explicitly address the integrated digital, data driven, and lifecycle-oriented demands associated with digitally transformed construction delivery. In parallel, a growing body of construction-focused research has highlighted that managing BIM-enabled, digitally integrated, and data-intensive project environments requires expanded competency sets spanning digital integration, behavioural leadership, governance, and technological coordination (Mandičák *et al.*, 2020; Liu *et al.*, 2022; Lukianov *et al.*, 2021; Atuahene *et al.*, 2023; Rodrigues *et al.*, 2023). Collectively, these studies demonstrate that digital transformation reshapes the role of the PM beyond traditional technical control functions.

Despite this, a critical research problem remains. Existing contributions typically identify digital PM competencies at an aggregated or thematic level, without systematically distinguishing between skills, knowledge, and core personality traits as analytically distinct competency domains. Much of the literature has focused on the conceptual articulation of digital PM competencies through qualitative, thematic, or framework-based approaches. While these studies provide important insights into the evolving competency landscape, relatively fewer studies have empirically examined how such competencies organise into distinct latent domains or how they relate to one another within a statistically validated structure. As a result, a structured and empirically validated competency framework that differentiates these core domains remains underdeveloped, an issue this study explicitly addresses.

To address this shortcoming, Owais *et al*. (2025) developed the Next-Gen Digital PM Competency List, comprising 55 competencies identified, categorised, and defined through a three-phase methodology integrating a Systematic Literature Review (SLR), NVivo-based thematic analysis, and Large Language Model (LLM) synthesis. Structured across the domains of Skills, Knowledge, and Core Personality Traits, this list offers a comprehensive foundation for understanding the multidimensional demands of digital project management. It was further validated through expert review and theoretically aligned with the functional requirements of DTs, thereby strengthening its conceptual robustness. However, a clear research gap remains while the Next-Gen Digital PM Competency List has been conceptually developed and theoretically validated, it has not yet been empirically tested to establish its latent structure, reliability, and generalisability. Without empirical synthesis, it remains unclear how these competencies cluster, interact, and form coherent capability domains in practice.

Building on this foundation, the present study employs Exploratory Factor Analysis (EFA) to empirically examine the underlying factor structure of the 55 competencies and synthesise them into a statistically validated framework. Accordingly, this paper addresses the following research question.

RQ. How can the identified, categorised, and defined digital project manager competencies be empirically synthesised into a validated framework that reveals their latent structure and reflects the competency demands of digitally transformed construction environments?

The contribution of this study is twofold. First, it advances the Next-Gen Digital PM Competency List by developing an empirically grounded framework that aligns with the requirements of advanced technologies such as DTs, BIM, IoT, and smart systems. Unlike prior qualitative or conceptual models, this study is among the first to provide a statistically validated framework of digital PM competencies specific to digitally transformed construction, advancing quantitative competency research in the built environment. Second, it establishes the foundation for confirmatory validation through Structural Equation Modelling (SEM) in subsequent research, thereby contributing to both academic theory and professional practice in digital project leadership.

2. Background and literature review

This section synthesises prior literature on digital construction project management by organising key competency themes related to BIM-enabled controls, leadership, risk and compliance, sustainability, automation, data management, and skills development.

2.1 BIM-enabled project controls in digital construction

Prior research consistently demonstrates that BIM enables enhanced project controls through digital scheduling, cost estimation, procurement, and resource coordination, particularly via integrated 4D and 5D BIM applications (Mesaros *et al*., 2020; Raza *et al*., 2023; Waqar *et al*., 2023). Within this stream, prior work in Smart and Sustainable Built Environment conceptualises BIM-based project success as a multidimensional outcome shaped by integrated information flows, coordination mechanisms, and organisational enablers, rather than technology adoption alone (Olugboyega *et al*., 2021). These digital capabilities support real-time integration of schedule and cost, automated quantity take-offs, and digitally enabled resource planning, allowing PMs to respond effectively to design changes and evolving project conditions (Liu *et al*., 2022; Rodrigues *et al*., 2023; Lee *et al*., 2021). Beyond time and cost control, BIM-enabled environments require PMs to resolve technical issues within digital models and coordinate interdisciplinary workflows, shifting their role from traditional plan controllers to coordinators of digitally mediated production systems across the project lifecycle (Mandičák *et al*., 2020; Omer *et al*., 2022; Uhm *et al*., 2017).

2.2 Leadership and stakeholder management in digitally enabled projects

Digital transformation has intensified the leadership role of PMs in coordinating multidisciplinary teams and diverse stakeholders within BIM-enabled project environments. Prior studies highlight team leadership, communication, emotional intelligence, and stakeholder engagement as essential for sustaining collaboration and performance in digitally mediated construction projects (Rodrigues *et al*., 2023; Liu *et al*., 2022; Omer *et al*., 2022). Effective leadership in these contexts also requires self-regulation, emotional resilience, and the ability to foster psychological safety and support team well-being under digitally intensive and dynamic working conditions (Mesaros *et al*., 2020; Kissi *et al*., 2025; Inguva *et al*., 2014; Omer *et al*., 2022).

2.3 Risk, safety, and compliance in digital project environments

The integration of digital technologies into construction projects has increased the importance of lifecycle-oriented risk management, safety planning, quality assurance, and regulatory compliance. Prior studies show that BIM-based safety simulations, automated checks, and digitally enabled governance mechanisms support proactive hazard identification, risk mitigation, and compliance across project stages (Liu *et al*., 2022; Kissi *et al*., 2025). Consistent with this perspective, prior work in Smart and Sustainable Built Environment highlights the role of integrated, information-driven approaches in enabling continuous and dynamic identification of project risks within digitally enabled construction environments (Moshtaghian *et al*., 2020). In parallel, digital tools facilitate continuous quality monitoring and contract administration by enabling data-driven oversight of standards, specifications, and contractual obligations throughout the project lifecycle, strengthening regulatory adherence and informed decision-making (Liu *et al*., 2022; Waqar *et al*., 2023; Inguva *et al*., 2014).

2.4 Sustainability and energy performance in smart construction

Sustainability-oriented competencies are increasingly embedded within digital project management practice, particularly through the use of BIM and DTs to support energy efficiency, carbon management, and lifecycle sustainability assessment. Prior studies demonstrate that digital technologies enable energy analysis, carbon footprint evaluation, and scenario-based design optimisation, allowing PMs to make informed decisions that reduce environmental impact and support environmentally responsible design choices while improving long-term building performance (Rodrigues *et al*., 2023; Waqar *et al*., 2023). In parallel, research highlights the growing importance of sustainability reporting and monitoring, where digital platforms facilitate the tracking, documentation, and communication of environmental performance to ensure transparency, regulatory alignment, and continuous improvement in smart construction projects (Rodrigues *et al*., 2023; Vuorikari *et al*., 2022).

2.5 Digital tools, automation, and technical capability

The effective use of advanced digital tools, automation, and technical systems has become a core capability for contemporary construction PMs operating in digitally enabled environments. Prior studies highlight increasing expectations for proficiency in BIM platforms, simulation tools, and integrated digital systems to support modelling, coordination, documentation, and data-driven decision-making across project phases (Lukianov *et al*., 2021; Uhm *et al*., 2017; Mandičák *et al*., 2020). In parallel, research points to the growing role of automation and AI-assisted programming in enhancing workflow efficiency, enabling customised digital solutions, and supporting innovation through the automation of repetitive tasks and the optimisation of project processes (Vuorikari *et al*., 2022; Kissi *et al*., 2025).

2.6 Data, documentation, and content management in BIM-based projects

As construction projects become increasingly data-driven, digital project management practice places growing emphasis on competencies related to data quality evaluation, structured documentation, and digital content management. Prior studies highlight the need for PMs to assess, validate, and analyse digital data generated through BIM and related platforms to support evidence-based decision-making and maintain reliable, up-to-date project information (Mandičák *et al*., 2020; Atuahene *et al*., 2023; Vuorikari *et al*., 2022). In parallel, research underscores the importance of cloud-based content management, version control, and structured information organisation to enable secure data storage, efficient collaboration, and lifecycle information continuity across digitally mediated projects (Lukianov *et al*., 2021; Lee *et al*., 2021). Beyond storage and access, digital content management capabilities also involve adapting and reusing digital assets to meet evolving project requirements, supporting efficient workflows and informed coordination in BIM-enabled environments (Vuorikari *et al*., 2022). Effective digital practice further requires structured digital documentation and archiving capabilities, including version control, file system management, and lifecycle information organisation, to ensure accuracy, accessibility, and continuity of project data within collaborative digital environments (Uhm *et al*., 2017).

2.7 Skills development and innovation for construction digital transformation

Prior literature consistently emphasises that successful digital transformation in construction depends on continuous digital skills development, innovation leadership, and the effective operationalisation of digital practices by PMs. Recent research in Smart and Sustainable Built Environment demonstrates that Industry 4.0 driven digital transformation in construction extends beyond technological adoption, with implementation strongly shaped by organisational change, human interaction, and evolving capability and skills requirements (Newman *et al*., 2021). Studies highlight the need for PMs to identify digital skill gaps, support targeted learning, and cultivate adaptive capabilities that enable teams to engage with emerging technologies and evolving digital workflows (Vuorikari *et al*., 2022; Lukianov *et al*., 2021). In parallel, research underscores the importance of innovation management competencies, whereby PMs lead the adoption of new digital solutions, overcome implementation barriers, and align technological change with organisational objectives (Rodrigues *et al*., 2023; Atuahene *et al*., 2023). Effective digital transformation further relies on strong digital communication and interaction capabilities to bridge technical and non-technical stakeholders, promote collaboration, and enable digitally enabled procurement processes as part of broader digital transformation initiatives, such as BIM-based quantity take-offs, cost coordination, and integration with scheduling and budgeting workflows, across project phases (Rodrigues *et al*., 2023; Mesaros *et al*., 2020; Raza *et al*., 2023).

3. Method

This study adopts a quantitative, cross-sectional survey design to empirically examine the latent structure of next-gen digital PM competencies in the construction sector. The target population comprised experienced Architecture, Engineering, and Construction (AEC) professionals actively engaged in digitally mediated project delivery across New Zealand and Australia. A purposive sampling strategy was employed to recruit information-rich participants with relevant digital project experience, resulting in a final analytical sample of 103 valid responses for EFA.

EFA was employed to empirically validate the Next-Gen Digital PM Competency List developed in earlier research (Owais *et al*., 2025). EFA is a multivariate statistical technique used to uncover the latent structure underlying a large set of observed variables by grouping them into coherent clusters, or factors, based on shared variance (Fabrigar *et al*., 1999; Costello and Osborne, 2005). It is particularly valuable in the early stages of framework or scale development when the dimensionality of constructs is not yet established (Worthington and Whittaker, 2006). In this study, EFA was applied to synthesise the 55 observed competency items into interpretable dimensions that capture the core structure of digital PM competencies required in technology-integrated construction environments.

As illustrated in Figure 1, the study followed a four-phase empirical strategy consistent with best-practice guidelines for quantitative validation (Hair *et al*., 2010; Kline, 2023). Phase 1 involved survey design and pilot testing to ensure the clarity and content validity of the measurement instrument. Phase 2 focused on sampling and participant recruitment among digitally engaged AEC professionals. Phase 3 applied EFA using Principal Axis Factoring (PAF) with Promax rotation to identify the latent structure underlying the 55 competency items. Finally, Phase 4 entailed interpretation and framework development, synthesising the extracted factors into a coherent model and establishing the foundation for confirmatory validation through SEM in future research.

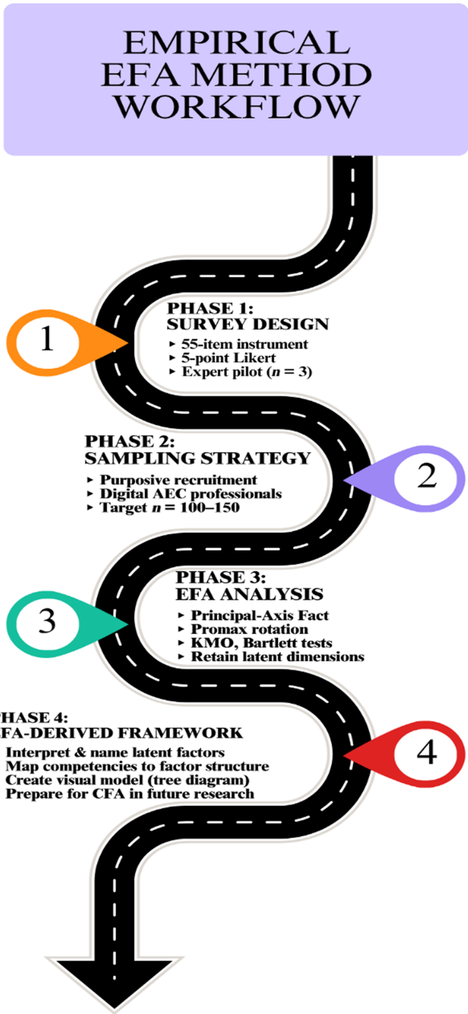

Figure 1. Empirical EFA method workflow. Source: Authors' own work

3.1 Phase one: survey design

To operationalise the validated Next-Gen Digital PM Competency List (Owais *et al.*, 2025), a structured survey instrument was designed to quantitatively assess the relative importance and latent structure of digital competencies in construction project management. The instrument comprised 55 items across three domains: Skills (26), Knowledge (21), and Core Personality Traits (8). Each item was phrased as a concise competency statement and rated on a five-point Likert scale (1 = Strongly Agree, 5 = Strongly Disagree), a format recognised for its psychometric robustness and suitability for factor analysis (DeVellis and Thorpe, 2022; Worthington and Whittaker, 2006).

To ensure content validity, the instrument underwent pilot testing with three domain experts (two academics and one industry-based digital PM). Their feedback informed minor refinements to phrasing and terminology. Representative items from each domain are shown in Table 1, demonstrating coverage of technical, cognitive, and behavioural dimensions. The final instrument was deployed via Qualtrics, ensuring secure and standardised data collection in accordance with the Auckland University of Technology Ethics Committee approval (AUTEC, reference number 23/257).

3.2 Phase two: sampling strategy

A purposive sampling approach was adopted, consistent with competency-validation research where the objective is to obtain information-rich insights rather than statistical generalisation (Palinkas *et al.*, 2015; Etikan *et al.*, 2016). The target population comprised experienced AEC professionals actively engaged in digitally mediated project delivery, such as digital PMs, BIM/VDC coordinators, engineers, site managers, and senior executives, across New Zealand and Australia.

Eligibility criteria required participants to have (1) at least five years of professional experience in AEC-related disciplines and (2) active involvement with digital tools and platforms such as BIM, DTs, cloud systems, or AI-enabled applications. These requirements ensured a respondent group that was both professionally mature and digitally competent.

Recruitment was carried out through professional associations, LinkedIn networks, digital construction forums, university–industry partnerships, and snowball referrals, ensuring diversity across roles, sectors, and regions (Robinson, 2014; Palinkas *et al.*, 2015). A target sample of 100–150 participants was set in accordance with EFA guidelines, which indicate that stable factor solutions can be achieved with $N \geq 100$ under conditions of high communalities and strong loadings (Costello and Osborne, 2005; Hair *et al.*, 2010; Wolf *et al.*, 2013).

To contextualise the dataset, demographic information, including age, gender, education, years of experience, role, discipline, and familiarity with digital technologies, was collected. These characteristics are reported in Section 4.4 to confirm sample representativeness and validate the recruitment approach.

Table 1. Representative survey items by competency domain

Domain	Sample competency item	Rating scale
Skills	Applying advanced digital tools (e.g. BIM, simulation tools) to design, model, and document deliverables	1 = Strongly Agree to 5 = Strongly Disagree
Knowledge	Understanding lifecycle data management and its role in digital project delivery and sustainability	1 = Strongly Agree to 5 = Strongly Disagree
Core personality traits	Demonstrating adaptability and emotional resilience under pressure in digitally dynamic environments	1 = Strongly Agree to 5 = Strongly Disagree

Source(s): Authors' own work

3.3 Phase three: EFA analysis

EFA was used to identify the latent structure underlying the 55 digital PM competencies developed and conceptually validated in earlier research (Owais *et al.*, 2025). These competencies were established through a rigorous three-phase process involving a SLR, NVivo-based thematic analysis, and LLM synthesis, followed by expert validation to ensure conceptual clarity and practical relevance. Nevertheless, their empirical dimensionality required statistical testing. EFA is widely applied in competency-validation studies because it reveals unobserved constructs that explain shared variance among observed variables, thereby supporting both construct development and theoretical alignment (Fabrigar *et al.*, 1999; Costello and Osborne, 2005; Worthington and Whittaker, 2006).

Prior to factor extraction, the dataset was examined for completeness, variability, and suitability. Cases with more than 15% missing responses were excluded, while item-level gaps were imputed using Expectation–Maximisation (EM), a recommended approach for maintaining structural relationships under missing-at-random conditions (Schafer and Graham, 2002; Enders, 2022). Standard Deviations (SDs) were screened to identify items with limited discriminatory power ($SD < 0.25$), though such items were retained if they carried strong theoretical importance (Morgado *et al.*, 2017).

Sampling adequacy was confirmed through the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity. KMO values ≥ 0.60 indicate acceptable shared variance, while a significant Bartlett's test ($p < 0.05$) confirms inter-item correlations suitable for factor analysis (Hair *et al.*, 2010; Field, 2024). Together, these diagnostics confirmed that the data met the statistical assumptions required for EFA.

For factor extraction, Principal Axis Factoring (PAF) was chosen over Principal Component Analysis (PCA) to identify latent constructs explaining shared variance rather than merely reducing dimensionality. PAF is also more robust to non-normal Likert-scale data (Fabrigar *et al.*, 1999; Field, 2024). To reflect the theoretical expectation that digital competencies are interrelated, an oblique Promax rotation was applied instead of orthogonal alternatives such as Varimax, thereby allowing factor correlations (Costello and Osborne, 2005).

Factor retention decisions were guided by four criteria.

(1) Eigenvalues ≥1.0 (Kaiser criterion);

(2) Visual inflection points in the scree plot;

(3) Conceptual coherence with the established competency list;

(4) A minimum of three items loading ≥0.40 on each factor, with no secondary loading ≥0.30 permitted.

Items not meeting these criteria were flagged for potential removal but carefully reviewed against the definitions in Owais *et al.* (2025), ensuring that statistical parsimony did not override conceptual fidelity (DeVellis and Thorpe, 2022). The final factor solution thus represents an empirically derived synthesis of the competency list, forming the foundation for the validated Next-Gen Digital PM Competency Framework presented in Section 5.

3.4 Phase Four: framework development

Based on the extracted factor structure, the retained factors were thematically interpreted to form the initial EFA-derived competency framework. Each factor was examined for conceptual coherence, and descriptive labels were assigned to capture its functional role in digital project management. Competency items were then mapped to their respective factors, producing a structured representation of the Next-Gen Digital PM Competency Framework.

This framework serves as an empirically grounded classification that bridges conceptual development and statistical validation, providing the basis for confirmatory testing through Confirmatory Factor Analysis (CFA) in subsequent research. While the framework highlights the competencies most representative of digital PM practice, those excluded during EFA remain relevant to specialised contexts and are acknowledged in the study's limitations.

4. Results and framework development

This section presents the empirical outcomes of the four-phase validation process outlined in Section 3. The primary objective is to empirically test and refine the Next-Gen Digital PM Competency List introduced in Owais *et al*. (2025), transforming it into an evidence-based framework that reflects the realities of digitally transformed construction environments. The results are presented by prioritising the core EFA outcomes (Phase 3) and the resulting empirically derived competency structure (Phase 4), followed by supporting descriptive statistics (Phase 1) and sample characteristics (Phase 2), consistent with established best practices in competency framework development and psychometric validation (Hair *et al*., 2010; Kline, 2023).

4.1 Phase three outcome: EFA results and competency factor structure

This section presents the outcomes of the EFA conducted to empirically examine the latent structure of the 55 digital PM competencies. The primary aim is to validate and refine the competency framework developed in Owais *et al*. (2025) by revealing statistically grounded latent dimensions across the three domains of Skills, Knowledge, and Core Personality Traits.

EFA was selected as a robust multivariate technique for identifying interrelationships among observed variables and uncovering underlying latent constructs that explain shared variance (Fabrigar *et al*., 1999; Costello and Osborne, 2005; Worthington and Whittaker, 2006). This phase employed PAF with Promax rotation, allowing factors to correlate in line with the theoretical assumption that digital PM competencies are interdependent. Prior to extraction, the dataset was screened for completeness, variability, and multivariate suitability as outlined in Section 3.3, ensuring all statistical assumptions were satisfied.

Factor retention followed a four-criteria approach integrating both statistical and theoretical considerations.

(1) Eigenvalues ≥1.0 (Kaiser criterion);

(2) Visual inspection of the scree plot to identify inflection points;

(3) Conceptual coherence with the established competency domains; and

(4) Minimum item-loading thresholds (≥0.40) with no secondary loadings ≥0.30.

These steps reflect recognised best-practice guidelines for construct development and psychometric validation (Worthington and Whittaker, 2006; Hair *et al*., 2010) and ensure the interpretability and reliability of the resulting factor solution.

This phase is structured into five subsections: Section 4.1.1 reports the KMO Measure and Bartlett's Test for Sampling Adequacy; Section 4.1.2 explains factor extraction and scree-plot analysis; Section 4.1.3 examines communalities and item adequacy; Section 4.1.4 presents the pattern matrix and factor loadings; and Section 4.1.5 addresses cross-loading diagnostics and item removal.

The validated factor structure presented in Section 5 constitutes the EFA-derived competency framework, forming the empirical foundation for confirmatory validation through SEM in subsequent research.

4.1.1 Kaiser–Meyer–Olkin and Bartlett's Test for Sampling Adequacy. Before conducting the EFA, the dataset's suitability for factor analysis was assessed using two standard diagnostics: the KMO Measure of Sampling Adequacy and Bartlett's Test of Sphericity. These tests evaluate whether the data structure is appropriate for uncovering latent factors through factor analysis.

The KMO statistic measures the proportion of variance among variables that may be common variance, reflecting the compactness of the correlation matrix. Values range from 0 to 1, with higher scores indicating stronger shared variance and greater factorability. According to Hair *et al*. (2010) and Field (2024), a KMO value of ≥0.60 is considered acceptable, 0.70–0.80 is good, and >0.80 is excellent. In this study, the overall KMO value was 0.736, confirming that the sample was adequate and suitable for factor extraction, as shown in Figure 2.

The Bartlett's Test of Sphericity examines whether the correlation matrix significantly deviates from an identity matrix, indicating that correlations among variables are sufficient to justify factor analysis (Hair *et al*., 2010). The test yielded a Chi-square (χ^2) value of 3579.238 with 1,485 degrees of freedom and a *p*-value <0.001, demonstrating that the inter-item correlations were statistically significant and appropriate for factor extraction.

Together, these diagnostic results confirm that the dataset met all assumptions required for EFA. The final sample of 103 valid responses demonstrated adequate intercorrelations for identifying underlying latent structures. A detailed summary of the KMO and Bartlett's test results is presented in Appendix 3 (Table A3) for reference and transparency.

4.1.2 Factor extraction and scree plot analysis. Following confirmation of data suitability, PAF was applied to the 55 competency items. The objective was to identify clusters of interrelated competencies representing latent constructs within the broader domains of Skills, Knowledge, and Core Personality Traits.

As discussed in Section 3.3, PAF was chosen over PCA because it is specifically designed to uncover latent constructs that explain shared variance among observed variables, rather than merely reduce dimensionality. PAF is particularly suited to psychometric research, where the goal is to model unobservable underlying traits that reflect theoretical constructs (Fabrigar *et al*., 1999; Costello and Osborne, 2005; Field, 2024). To determine the optimal number of factors to retain, a four-criteria approach was employed, as outlined in Section 4.1.

In this analysis, λ (lambda) denotes eigenvalues and Δ (delta) represents the difference between successive eigenvalues. Following these criteria, the initial extraction retained 15 factors with eigenvalues greater than 1.0, as shown in Table 2.

While eigenvalues (λ) ≥ 1.0 indicate statistical significance (DeVellis and Thorpe, 2022), statistical thresholds alone can be misleading if interpreted without theoretical context (Costello and Osborne, 2005). As illustrated in the scree plot, Figure 3, the curve shows a distinct inflection, or "elbow," at Factor 8, after which the eigenvalues level off substantially. Notably, Factor 7 ($\lambda = 1.696$) and Factor 8 ($\lambda = 1.521$) exhibited only a marginal decline ($\Delta = 0.175$). According to Auerswald and Moshagen (2019), such minimal differences suggest limited additional explanatory gain. Accordingly, a seven-factor solution was adopted to maintain parsimony and theoretical coherence.

The decision to retain seven factors was further reinforced by their close alignment with the conceptual definitions established in the digital PM competency list. Several extracted factors consisted entirely of items from a single domain, Skills, Knowledge, or Core Personality Traits, demonstrating strong empirical consistency with the theoretical structure. This domain-specific clustering supports the structural validity of the survey instrument and confirms that observed patterns of association reflect the conceptual distinctions established in prior research.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.736
Bartlett's Test of Sphericity	Approx. Chi-Square	3579.238
	df	1485
	Sig.	<0.001

Figure 2. KMO and Bartlett's test output. Source: Authors' own work

Table 2. Extracted factors with eigenvalues ≥1.0

Total variance explained Initial eigenvalues				Extraction sums of squared loadings		
Factor	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	14.506	26.375	26.375	14.157	25.739	25.739
2	3.996	7.265	33.640	3.648	6.633	32.372
3	3.170	5.763	39.404	2.808	5.105	37.478
4	2.438	4.433	43.837	2.078	3.779	41.257
5	2.335	4.245	48.081	1.989	3.616	44.873
6	2.104	3.825	51.906	1.759	3.198	48.071
7	1.696	3.083	54.989	1.330	2.418	50.489
8	1.521	2.766	57.755	1.155	2.100	52.588
9	1.421	2.583	60.338	1.074	1.953	54.541
10	1.405	2.554	62.892	1.045	1.901	56.442
11	1.246	2.265	65.157	0.910	1.655	58.097
12	1.193	2.169	67.326	0.838	1.523	59.620
13	1.153	2.097	69.422	0.801	1.456	61.077
14	1.081	1.965	71.388	0.723	1.314	62.391
15	1.017	1.849	73.237	0.663	1.206	63.597

Source(s): Authors' own work

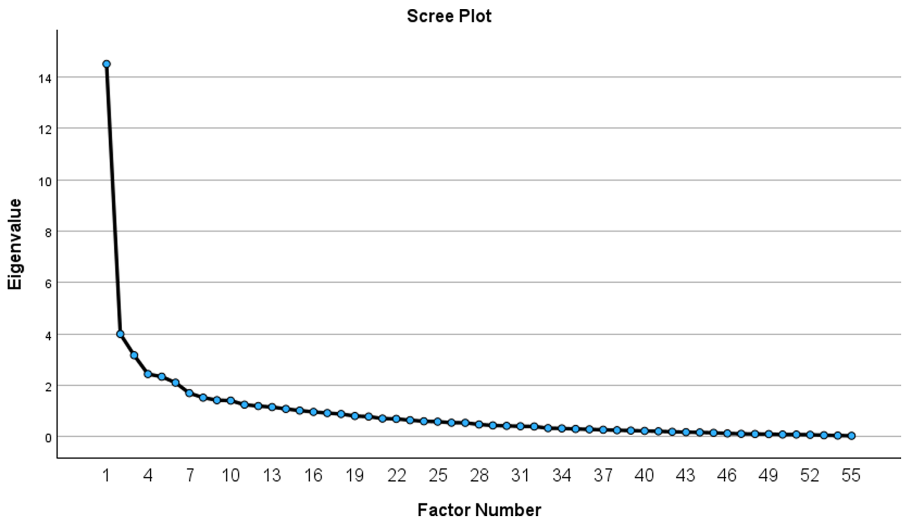

Figure 3. Scree plot of extracted factors from EFA. Source: Authors' own work

As summarised in Table 3, the seven retained factors collectively explained 54.989% of the total variance, a proportion well within the acceptable range for social-science research (Worthington and Whittaker, 2006; Hair *et al.*, 2010). The complete variance output is provided in Appendix 4 (Table A4) for transparency.

The integration of empirical indicators (λ ≥ 1.0, Δ ≈ 0.175) with theoretical justification strengthens both the construct validity and interpretability of the factor solution. The following section (4.1.3) examines item-level communalities and variance contributions to further evaluate the adequacy of the extracted factors.

Table 3. Total variance explained by the seven extracted factors (Initial extraction – full item set)

Factor	Initial eigenvalue	% of variance	Cumulative %
1	14.506	26.375	26.375
2	3.996	7.265	33.640
3	3.170	5.763	39.404
4	2.438	4.433	43.837
5	2.335	4.245	48.081
6	2.104	3.825	51.906
7	1.696	3.083	54.989

Source(s): Authors' own work

4.1.3 Communalities and item adequacy. Following the decision to retain a seven-factor solution (Section 4.1.2), communalities were recalculated using PAF with extraction fixed to seven factors to obtain precise estimates of each item's shared variance within the final framework. Communality denotes the proportion of an item's variance explained by the retained factors. Consistent with Field (2024) and Hair *et al*. (2010), values ≥ 0.30 are considered acceptable, while lower values warrant scrutiny for weak structural contribution or conceptual misalignment.

As reported in Appendix 5 (Table A5): Communalities of Extracted Factors, SPSS communalities across the 55 digital PM items ranged from 0.264 to 0.681, indicating that the seven-factor solution captured meaningful shared variance for most items. Specifically.

(1) *28 items* showed communalities >0.500, evidencing strong explanatory power and clear factor alignment.

(2) *23 items* fell between 0.300–0.499, an acceptable range in exploratory research when theoretically grounded (Worthington and Whittaker, 2006).

(3) *Four items*, K21 (0.264), K10 (0.290), S21 (0.296), and S13 (0.292), were slightly below the 0.30 threshold.

Rather than exclude these four borderline items outright, their theoretical relevance and behaviour in the rotated solution were assessed in light of their conceptual definitions from the validated competency list (Owais *et al*., 2025).

(1) *K21*, the lowest by communality, was retained for its role in capturing Digital Knowledge Integration in Construction; its removal would create a gap in the Knowledge domain.

(2) *K10* and *S21* showed acceptable primary loadings in the pattern matrix (Section 4.1.4) and no cross-loadings; both represent essential but context-sensitive digital PM capabilities.

(3) *S13* (Digital Technologies Training and Development) is central to capacity-building and knowledge transfer; its slightly low communality likely reflects role-based variation rather than weak construct coherence.

This approach follows Costello and Osborne (2005), who caution against letting strict numeric cut-offs override construct validity in social-science scale development. Retaining theoretically vital borderline items preserves conceptual completeness and practical relevance. Overall, the communalities profile confirms item adequacy and factor coverage, justifying carrying all 55 items forward to the rotated pattern-matrix stage, as illustrated in the next section.

4.1.4 Pattern matrix and factor structure. The final rotated pattern matrix reports the unique pattern coefficients of each retained item on the seven latent factors after accounting for factor intercorrelations (Fabrigar *et al.*, 1999; Hair *et al.*, 2010). Following established conventions, items with primary loadings ≥0.40 were treated as meaningful indicators, while cross-loadings ≥0.30 were taken as evidence of ambiguity and therefore disallowed (Worthington and Whittaker, 2006, DeVellis and Thorpe, 2022).

No retained items exhibited cross-loadings ≥0.30, yielding a clean, well-differentiated structure that strengthens discriminant validity, reduces the risk of CFA misspecification, and supports confirmatory testing within the SEM framework (Costello and Osborne, 2005; Kline, 2023). While the vast majority exceeded the 0.40 threshold, S10 (0.369) and S16 (0.378) were retained on conceptual grounds and for strong thematic coherence with their respective factors; modestly sub-threshold loadings can be justified when they enhance construct completeness (Worthington and Whittaker, 2006).

All retained competencies correspond to the validated Next-Gen Digital PM Competency List established through prior systematic research (Owais *et al.*, 2025). These competencies reflect recurring themes widely reported in the construction digital transformation literature, including BIM-enabled project controls (e.g. digital scheduling, cost, and resource coordination) (Mesaros *et al.*, 2020; Raza *et al.*, 2023; Waqar *et al.*, 2023), leadership and stakeholder management in BIM- and smart-enabled environments (Rodrigues *et al.*, 2023; Omer *et al.*, 2022), lifecycle risk, safety, and compliance knowledge (Liu *et al.*, 2022; Kissi *et al.*, 2025), sustainability and energy-performance-related competencies in smart construction (Rodrigues *et al.*, 2023; Waqar *et al.*, 2023), digital capability and automation in project management roles (Lukianov *et al.*, 2021; Uhm *et al.*, 2017), digital content and data management (Mandičák *et al.*, 2020; Atuahene *et al.*, 2023), and skills development and innovation for digital transformation (Rodrigues *et al.*, 2023; Lukianov *et al.*, 2021).

Through EFA, these literature-identified themes are empirically synthesised into a set of latent competency factors grounded in observed response patterns. The final rotated pattern matrix of retained competencies is presented in Table 4, followed by detailed interpretation of each extracted factor. Each factor represents an empirically derived configuration of digital project management capabilities while remaining conceptually anchored in the dominant competency domains identified in the literature.

(1) Factor 1: Digital Execution and Optimisation

Factor 1 comprises five skill-based competencies, S3, S22, S20, S23, and S15, centred on data-informed, systems-driven delivery in complex environments.

- *S3. Digital building performance optimisation:* Strategic use of advanced digital technologies such as BIM to enhance operational and environmental performance across the building lifecycle; continuous monitoring and optimisation to improve energy efficiency, durability, and asset value.
- *S22. Digital scheduling management:* Synchronising time-related project data with digital workflows (e.g. 4D BIM) to visualise sequencing, adjust timelines in real time, and achieve proactive schedule control.
- *S20. Real-time cost optimisation and digital budgeting:* Applying tools such as 5D BIM and advanced cost-tracking for accurate budgeting, forecasting, and financial responsiveness; supports automated take-offs, cost analysis, and real-time decision support.
- *S23. Digital resource management:* Coordinating labour, materials, and digital assets via centralised platforms; aligning resource allocation with schedule and budget to enhance productivity and sustainability.

Table 4. Rotated pattern matrix of retained competencies

Pattern matrix[a] Factor Competency	1	2	3	4	5	6	7
S3	0.887						
S22	0.745						
S20	0.597						
S23	0.546						
S15	0.495						
CP5		0.763					
CP1		0.719					
CP3		0.660					
CP2		0.568					
K7			0.766				
K8			0.729				
K6			0.448				
K19				0.774			
K17				0.689			
K18				0.687			
S11					0.690		
S12					0.508		
S14					0.477		
S7						0.832	
S8						0.543	
S10						0.369	
S21							0.621
S4							0.599
S26							0.438
S16							0.378

Note(s): Extraction Method: Principal Axis Factoring,
Rotation Method: Promax with Kaiser Normalisation, [a]Rotation converged in 8 iterations
Source(s): Authors' own work

- *S15. Digital problem solving and technical support:* Troubleshooting platform issues, supporting software implementation, and fostering innovation through adaptive, technical problem solving.

Collectively, these competencies form a coherent cluster centred on the optimisation of cost, time, quality, and resources within dynamic project environments. The factor is termed *Digital Execution and Optimisation*, representing a practically oriented pillar fully aligned with the Skills domain (Owais *et al*., 2025). This finding is consistent with prior studies highlighting BIM-enabled project controls, real-time schedule cost integration, and digitally mediated resource coordination as central capabilities for construction PMs in digital delivery contexts (Mesaros *et al*., 2020; Raza *et al*., 2023; Waqar *et al*., 2023; Liu *et al*., 2022), as discussed in Section 2.1.

(2) Factor 2: Human-centred digital leadership

Includes four competency items from the Core Personality Traits domain: CP1, CP2, CP3, and CP5. These competencies capture the behavioural, emotional, and interpersonal capacities vital for leadership in collaborative digital environments.

- *CP1. Team leadership in digital construction:* Ability to lead multidisciplinary teams in virtual construction environments, such as BIM or DT-mediated settings, through trust-building, mentoring, and conflict resolution.

- *CP2. Stakeholder leadership in digital construction:* Extending leadership to clients, regulators, and end users; leveraging digital tools for transparency and engagement.
- *CP3. Digital self-leadership and emotional agility:* Emotional regulation, resilience, and emotional intelligence in high-pressure, tech-rich projects
- *CP5. Team well-being leadership:* Promoting psychological safety, morale, and well-being within digital or hybrid teams, supporting sustainable human performance.

Collectively, these competencies define a human-centred behavioural dimension essential for effective digital collaboration. The factor is termed *Human-Centred Digital Leadership*, representing an empirically validated pillar of the Core Personality domain. This factor is consistent with prior literature emphasising leadership, emotional intelligence, and stakeholder engagement as critical capabilities for managing digitally enabled construction projects, particularly within BIM-mediated and collaborative environments (Rodrigues *et al*., 2023; Liu *et al*., 2022; Omer *et al*., 2022), as discussed in Section 2.2.

(3) Factor 3: Lifecycle risk and compliance knowledge

Factor 3 consists of three knowledge-based competencies: K7, K8, and K6. These represent strategic and operational knowledge for managing quality, contracts, and safety throughout the project lifecycle.

- *K7. Digital quality assurance and lifecycle management:* Integration of quality control with lifecycle thinking using digital platforms to track compliance, analyse performance data, and drive continuous improvement that supports a proactive approach to digital assurance.
- *K8. Contract and negotiation management:* Addresses legal and regulatory dimensions of contract administration, including negotiation, compliance, and dispute resolution aligned with digital workflows and contractual frameworks, ensuring transparency, accountability, and relationship management across stakeholders.
- *K6. Digital safety and risk mitigation:* Application of digital tools to enhance safety planning and risk reduction throughout the project lifecycle. It includes BIM-enabled hazard detection, simulation of safety scenarios, and automated compliance monitoring.

Together, these competencies form a governance-oriented cluster uniting quality, contractual, and safety oversight in data-driven project ecosystems. The factor is termed *Lifecycle Risk and Compliance Knowledge*, within the Knowledge domain. This factor aligns with prior research highlighting lifecycle-oriented risk management, digital safety planning, quality assurance, and contract governance as central knowledge areas for construction PMs operating in digitally enabled environments (Liu *et al*., 2022; Kissi *et al*., 2025; Waqar *et al*., 2023; Inguva *et al*., 2014), as discussed in Section 2.3.

(4) Factor 4: Digital sustainability intelligence

Factor 4 includes three knowledge-based competencies, K19, K17, and K18, that embed sustainability within digital project delivery.

- *K19. Sustainable construction strategies:* Focuses on embedding sustainability across project planning and execution using digital tools to support green design and material selection. Through technologies such as BIM-based lifecycle assessment, digital PMs promote environmentally responsible and resilient construction practices.
- *K17. Energy efficiency and carbon management:* Optimising energy use and reducing carbon emissions through advanced tools such as BIM- or DT-enabled simulations,

monitoring, and performance analytics to enhance sustainability-driven decision-making during design and construction.

- *K18. Sustainability reporting and monitoring:* Tracking and communicating environmental performance via measurable indicators and transparent reporting that supports continuous improvement in digital sustainability performance.

This knowledge cluster positions sustainability as a core digital PM responsibility. The factor is termed *Digital Sustainability Intelligence*, confirming sustainability knowledge as a distinct and empirically validated domain of the digital PM competency list. This factor is consistent with prior studies emphasising the role of BIM and DTs in supporting sustainability intelligence through energy analysis, carbon management, and lifecycle performance monitoring, positioning sustainability reporting and optimisation as core knowledge requirements for digitally enabled construction project management (Rodrigues *et al.*, 2023; Waqar *et al.*, 2023; Vuorikari *et al.*, 2022), as discussed in Section 2.4.

(5) Factor 5: Digital tools proficiency and automation

Factor 5 comprises three skill-based competencies, S11, S12, and S14, that reflect technical fluency in automating workflows and managing digital systems.

- *S11. AI-assisted programming and automation:* Designing programmable or automated solutions to streamline workflows and embed innovation into core project functions. It includes proficiency in coding, data analysis, and the development of tailored software-based functions to automate repetitive tasks or solve domain-specific challenges.
- *S12. Smart construction digital tool utilisation:* Effective and creative use of digital applications such as BIM, CAD, and simulation platforms to enhance collaboration, accuracy, and sustainability integration. It reflects the PM's ability to align digital tool outputs with technical standards, energy modelling requirements, and sustainable objectives, thereby supporting the seamless integration of digital technologies into construction practices.
- *S14. Smart digital documentation and archiving:* Structured management of digital files using digital tools such as BIM and CAD, ensuring version control, defined documentation protocols, and long-term data accessibility across project phases and stakeholders.

Together, these competencies define a skill cluster focused on digital tool mastery, automation, and disciplined data management. The factor is termed *Digital Tools Proficiency and Automation*, confirming strong alignment with the Skills domain. This factor aligns with prior studies identifying digital tool proficiency, automation, and structured documentation as core technical capabilities for construction PMs in digitally enabled environments (Lukianov *et al.*, 2021; Vuorikari *et al.*, 2022; Uhm *et al.*, 2017), as discussed in Section 2.5.

(6) Factor 6: Digital content and data management

This factor comprises three skill-based competencies, S7, S8, and S10, that emphasise data integrity, collaboration, and innovation in digital information workflows.

- *S7. Digital data evaluation and analytics:* Verification, analysis, and visualisation of project data in real time using digital platforms to support evidence-based decisions and maintain accurate, up-to-date models.
- *S8. Cloud-based digital content management:* Secure organisation of cloud-based repositories with standardised data-processing, responsible information-sharing, and collaborative access protocols across distributed teams.

- *S10. Advanced digital content management:* Adaptive reuse and refinement of digital content to generate new deliverables, enhancing innovation, efficiency, and resource optimisation across digital project teams.

Together, these competencies constitute a cohesive skill cluster around data stewardship and content innovation. The factor is termed *Digital Content and Data Management*, confirming its structural and conceptual coherence within the Skills domain. This factor is consistent with prior research emphasising data quality evaluation, cloud-based content management, and adaptive reuse of digital information as essential capabilities for evidence-based decision-making and collaboration in BIM-enabled project environments (Mandičák *et al.*, 2020; Atuahene *et al.*, 2023; Vuorikari *et al.*, 2022), as discussed in Section 2.6.

(7) Factor 7: Digital transformation enablement skills

Factor 7 includes four skill-based competencies: S21, S4, S26, and S16. These represent the strategic capabilities required to enable digital transformation across projects and teams.

- *S21. Automated digital procurement management:* Integration of cost estimation and procurement tools (e.g. 5D BIM) to enable transparent, data-driven acquisition processes and stronger alignment between design, budgeting, and supply-chain operations.

- *S4. Digital communication and interaction strategies:* Bridging technical and non-technical audiences through adaptive communication that fosters collaboration and trust across virtual, hybrid, and on-site contexts.

- *S26. Innovation management in digital construction:* Leading the adoption of emerging technologies such as AI, automation, and big data to embed a culture of innovation aligned with project goals and industry transformation.

- *S16. Digital skills gap analysis and development:* Assessing digital proficiency and enhancing maturity at team and organisational levels through targeted upskilling, strategic learning pathways, and digital engagement initiatives.

Together, these competencies form a transformation-oriented skill cluster that enables PMs to drive operational optimisation, innovation, and long-term digital capability. The factor, termed *Digital Transformation Enablement Skills*, captures the digital PM's evolving role in leading people, processes, and technologies toward adaptive and future-ready practices. This factor is consistent with prior studies identifying digital skills development, innovation leadership, adaptive communication, and digitally enabled procurement as key enablers of construction digital transformation (Rodrigues *et al.*, 2023; Vuorikari *et al.*, 2022; Lukianov *et al.*, 2021; Atuahene *et al.*, 2023; Mesaros *et al.*, 2020).

The seven empirically derived factors demonstrate strong thematic cohesion and clear domain-level alignment across the Skills, Knowledge, and Core Personality Trait domains, confirming the structural validity of the Next-Gen Digital PM Competency Framework. The resulting clean pattern matrix indicates a robust and interpretable factor solution, supporting both the theoretical grounding and measurement integrity of the instrument. The following section outlines the treatment of cross-loadings and item removal decisions applied during the EFA process to enhance factor distinctiveness, parsimony, and conceptual clarity.

4.1.5 Cross-loadings and item removal. To ensure conceptual clarity and statistical robustness, this section presents the cross-loading assessment and item removal decisions undertaken during the EFA process. The central aim was to reinforce the discriminant validity and conceptual distinctiveness of each extracted factor by removing items that exhibited ambiguous loading patterns, thematic redundancy, or insufficient contribution. These refinements enhanced parsimony and improved the framework's readiness for subsequent validation through CFA.

In EFA, a cross-loading is typically defined as a secondary loading ≥0.30 on a non-primary factor (Costello and Osborne, 2005; Worthington and Whittaker, 2006). Such items may lack a clear conceptual home, compromise interpretability, and reduce factor distinctiveness. While the final rotated pattern matrix revealed a clean and well-defined structure with no problematic cross-loadings, earlier extraction rounds identified items requiring removal under specific criteria, including.

(1) Cross-loadings ≥0.30 on multiple factors, compromising discriminant validity.

(2) Insufficient loading strength, where the item failed to meet the recommended 0.40 threshold on any single factor (Worthington and Whittaker, 2006; Hair *et al*., 2010).

(3) Conceptual redundancy, where content overlapped with other items offering stronger factor representation.

(4) Ambiguous thematic alignment, where competencies did not clearly map onto emergent latent constructs.

Table 5 summarises the competencies removed during the iterative refinement process, along with concise justifications. All listed competencies originate from the validated Next-Gen Digital PM Competency List developed through prior systematic research (Owais *et al*., 2025; see Appendix 1 (Table A1)), where their conceptual definitions and primary supporting references are fully documented. For transparency, Table 5 provides one indicative reference per removed competency, while the complete set of foundational sources for each item is traceable to Appendix 1 (Table A1). Their removal in the present study reflects empirical refinement decisions based on EFA diagnostics rather than a lack of theoretical or practical relevance.

Although these 30 competencies were excluded from the final factor structure, their relevance to digital project management remains significant. Each reflects a specialised domain that may not have emerged as a statistically distinct factor within this study but still contributes meaningfully to broader professional practice. Their removal reflects a methodological focus on achieving construct precision, parsimony, and discriminant validity rather than questioning their conceptual importance. Future research may revisit these competencies in more specialised or extended frameworks, such as cybersecurity, AI integration, training design, or validate them through larger and more diverse samples using techniques such as Delphi studies. The outcome of this refinement process produced a parsimonious and statistically robust framework of 25 retained competencies across seven latent constructs. Together, these empirically validated clusters form the Next-Gen Digital PM Competency Framework, representing the empirically validated foundation for confirmatory testing through CFA and subsequent SEM analysis.

4.2 Phase four outcome: empirically derived competency structure for digital PMs

This section presents the final outcome of Phase Four, which involved interpreting and consolidating the EFA results into a structured competency framework. Drawing on the validated pattern matrix and factor structure detailed in the preceding analysis, seven latent factors were retained, comprising a total of 25 competency items. These groupings represent empirically derived clusters of digital PM competencies that converge around shared statistical patterns and thematic alignment, reflecting the underlying structure of digital capability requirements in the evolving construction sector.

Each factor was named according to the shared conceptual focus of its underlying competencies. The resulting structure spans the full competency list developed in the earlier stages of this research and aligns with the theoretical framework established earlier, encompassing the three core domains of Skills, Knowledge, and Core Personality Traits. This alignment confirms the theoretical relevance of the original framework and supports its empirical validity through factor-analytic evidence.

Table 5. Competencies removed during EFA refinement (Originally defined in Owais *et al.*, 2025)

Code	Competency name	Reason for removal
S1	Advanced Digital Technology Proficiency (e.g. Rodrigues *et al.*, 2023)	Cross-loaded across multiple technical and strategic factors; lacked distinct thematic anchoring
S2	Digital Technology Integration (e.g. Liu *et al.*, 2022)	Overlapped conceptually with several integration and execution items; reduced factor specificity
S5	Real-Time Digital Information Exchange (e.g. Vuorikari *et al.*, 2022)	Demonstrated ambiguous loadings; content overlapped with communication and data management clusters
S6	Digital Collaboration and Knowledge Retention (e.g. Lukianov *et al.*, 2021)	Cross-loaded with both communication and innovation-related factors; weakened discriminant validity
S9	Digital Content Development Skills (e.g. Vuorikari *et al.*, 2022)	Shared variance with data handling and tool utilisation; lacked a clean loading path
S13	Digital Technologies Training and Development (e.g. Hosseini *et al.*, 2018)	Diffused across upskilling and leadership factors; failed to stabilise on a single factor
S17	Cybersecurity and Digital Device Protection (e.g. Atuahene *et al.*, 2023)	Cross-loaded across risk and IT clusters; remained statistically weak
S18	Digital Privacy and Data Protection Compliance (e.g. Lee *et al.*, 2021)	Conceptually overlapped with legal and governance items; cross-loaded during analysis
S19	Emerging Technologies Cost Management (e.g. Rodrigues *et al.*, 2023)	Ambiguous loading between cost and innovation clusters; lacked unique conceptual identity
S24	Digital Quality Control (e.g. Raza *et al.*, 2023)	Overlapped with broader lifecycle assurance items; diluted factor interpretability
S25	Digital Scope and Change Management (e.g. Kissi *et al.*, 2025)	Loaded across scheduling, planning, and execution clusters; created factor ambiguity
K1	Advanced Digital Construction Knowledge (e.g. Mandičák *et al.*, 2020)	Broad theoretical scope resulted in diffuse loadings; insufficient specificity
K2	Emerging Technology Integration Knowledge (e.g. Inguva *et al.*, 2014)	Shared conceptual ground with innovation and technical domains; cross-loading prevented clean alignment
K3	Smart Systems and Applications Knowledge (e.g. Waqar *et al.*, 2023)	Cross-loaded with digital tools and automation competencies; lacked singular factor fit
K4	Digital Project Strategy and Goal Alignment (e.g. Mesaros *et al.*, 2020)	Spread across leadership and governance domains; failed to anchor thematically
K5	Digital Project Integrated Management (e.g. Raza *et al.*, 2023)	Statistically unstable; overlapped with multiple project execution constructs
K9	Regulatory and Compliance (e.g. Uhm *et al.*, 2017)	Cross-loaded with contract and governance factors; lacked distinct empirical support
K10	Language Proficiency (e.g. Liu *et al.*, 2022)	Thematically relevant but isolated; weak factor convergence
K11	Digital Information and Data Literacy (e.g. Lukianov *et al.*, 2021)	Distributed across multiple knowledge areas; lacked a coherent empirical grouping
K12	Digital Construction Risk Management (e.g. Rodrigues *et al.*, 2023)	Cross-loaded with safety, legal, and strategic knowledge domains; compromised clarity
K13	Digital Technology Adoption Risk Mitigation (e.g. Atuahene *et al.*, 2023)	Shared conceptual ground with innovation and risk domains; failed to align cleanly
K14	Financial Risk Management (e.g. Rodrigues *et al.*, 2023)	Overlapped with budgeting and lifecycle management items; blurred loading pattern
K15	AI-Powered Data-Driven Decision-Making (e.g. Lukianov *et al.*, 2021)	Cross-loaded across analytics and leadership factors; lacked statistical isolation
K16	Standardising Digital Technology Processes (e.g. Hosseini *et al.*, 2018)	Overlapped with implementation and governance domains; failed to stabilise in one factor
K20	Qualifications and Professional Development (e.g. Liu *et al.*, 2022)	Conceptually diffuse; weak empirical alignment with any emergent factor
K21	Curriculum Development (e.g. Uhm *et al.*, 2017)	Retained low communality and failed to cluster strongly; removed despite relevance

(*continued*)

Table 5. Continued

Code	Competency name	Reason for removal
CP4	Decision-Making and Accountability (e.g. Omer *et al.*, 2022)	Cross-loaded with leadership and governance traits; impaired construct clarity
CP6	Digital Team Communication and Collaboration (e.g. Mandičák *et al.*, 2020)	Statistically unstable; overlapped with broader team coordination constructs
CP7	Digital Stakeholder Communication and Collaboration (e.g. Kissi *et al.*, 2025)	Cross-loaded between stakeholder management and digital communication factors
CP8	Digital Innovation and Creativity in Smart Construction (e.g. Lukianov *et al.*, 2021)	Diffused across multiple innovation and personality factors; lacked clean empirical fit

Source(s): Authors' own work

Table 6 summarises the final seven-factor solution, including factor names, associated competencies, and the percentage of variance explained, based on the final output from PAF with Promax rotation.

Together, these seven latent factors capture the multidimensional nature of digital PM competencies within the construction sector's ongoing digital transformation. They represent a balanced integration of technical, cognitive, and behavioural domains, offering a statistically validated foundation for the Next-Gen Digital PM Competency Framework. This empirically grounded structure provides a robust basis for subsequent confirmatory validation through CFA and SEM in future research.

4.3 Phase one outcome: primarily descriptive statistics and data screening

Descriptive statistics were computed for all 55 competency items to evaluate their psychometric suitability and confirm the dataset's readiness for latent variable analysis as part of the empirical validation of the Next-Gen Digital PM Competency List. Each item was rated on a five-point Likert scale (1 = Strongly Agree, 5 = Strongly Disagree). The analysis examined measures of central tendency, variability, and distribution shape to ensure that the dataset satisfied the assumptions required for EFA.

4.3.1 Mean, min, and max. The mean reflects the central tendency of responses, while minimum and maximum values highlight the spread of agreement across participants. A wide response range, particularly when paired with low mean values (anchored at 1 = Strongly Agree), indicates both strong endorsement and sufficient variability for factor analysis (DeVellis and Thorpe, 2022; Field, 2024).

Table 6. Final retained factors, competencies, and variance explained

Factor	Factor name	Retained competencies	% variance explained
1	Digital Execution and Optimisation	S3, S22, S20, S23, and S15	25.789%
2	Human-Centred Digital Leadership	CP5, CP1, CP3, and CP2	8.460%
3	Lifecycle Risk and Compliance Knowledge	K7, K8, and K6	6.347%
4	Digital Sustainability Intelligence	K19, K17, and K18	4.404%
5	Digital Tools Proficiency and Automation	S11, S12, and S14	3.542%
6	Digital Content and Data Management	S7, S8, and S10	2.927%
7	Digital Transformation Enablement Skills	S21, S4, S26, and S16	2.088%
			Total = 53.556%

Source(s): Authors' own work

In the Skills domain, Figure 4, mean values ranged between 1.50 and 2.02 across the 26 competencies. Items such as S3. Digital Building Performance Optimisation, S10. Advanced Digital Content Management, and S21. Automated Digital Procurement Management scored particularly high in importance. All items recorded a minimum value of 1, with maximum values between 4 and 5, demonstrating adequate variability.

In the Knowledge domain, mean ratings across the 21 competencies ranged from 1.61 to 2.15, indicating strong consensus regarding their importance, as shown in Figure 5. Minimum values were consistently 1, and maximum scores of 5 were recorded for multiple items, confirming both high endorsement and sufficient response variability to support latent structure analysis.

For the Core Personality Traits domain, mean ratings across the eight behavioural competencies, as illustrated in Figure 6, ranged from 1.43 to 1.99, indicating strong consensus

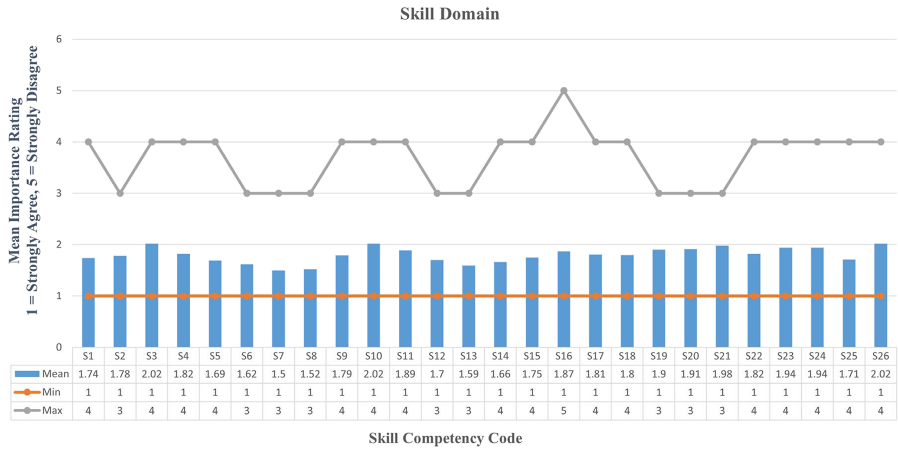

Figure 4. Skills competency descriptive statistics: mean, min, max. Note: Full competency definitions are provided in Owais *et al.* (2025), Appendix 3 (Table A3). Source: Authors' own work

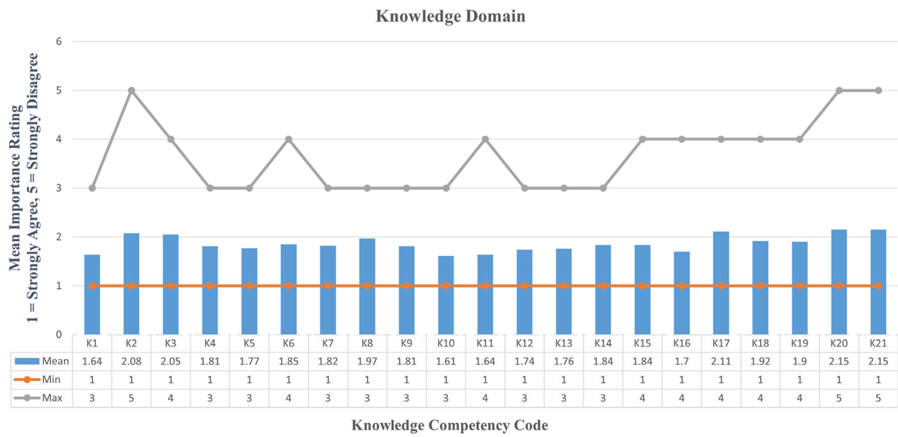

Figure 5. Knowledge competency descriptive statistics: mean, min, max. Note: Full competency definitions are provided in Owais *et al.* (2025), Appendix 3 (Table A3). Source: Authors' own work

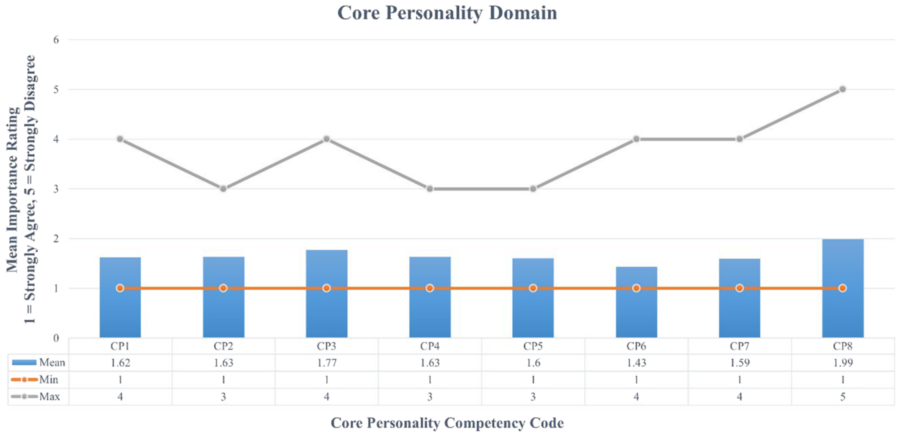

Figure 6. Core personality traits descriptive statistics: mean, min, max. Note: Full competency definitions are provided in Owais *et al*. (2025), Appendix 3 (Table A3). Source: Authors' own work

on the importance of adaptability, resilience, and leadership-oriented traits. Minimum values were consistently 1, while maximum values ranged from 3 to 5, confirming adequate response variability and justifying their inclusion in subsequent analyses.

4.3.2 Standard deviation and response variability screening. SD values were calculated at the respondent level across all 55 competency items to detect inattentive or invalid response patterns (Meade and Craig, 2012; Clark and Watson, 2016; DeSimone *et al.*, 2015). Low variability can indicate uniform answering (e.g. selecting "1 – Strongly Agree" throughout), which can artificially inflate inter-item correlations and bias factor extraction. A commonly adopted threshold of SD < 0.25 was applied to flag cases with insufficient response variability (Curran, 2016; Huang *et al.*, 2012).

A total of eight respondents fell below this threshold and were excluded from further analysis to maintain data quality. The remaining 103 valid cases, arranged in descending order, demonstrated acceptable variability, with SD values ranging from 0.2672 to 1.0899. As shown in Figure 7, this distribution confirms adequate participant engagement and discriminative

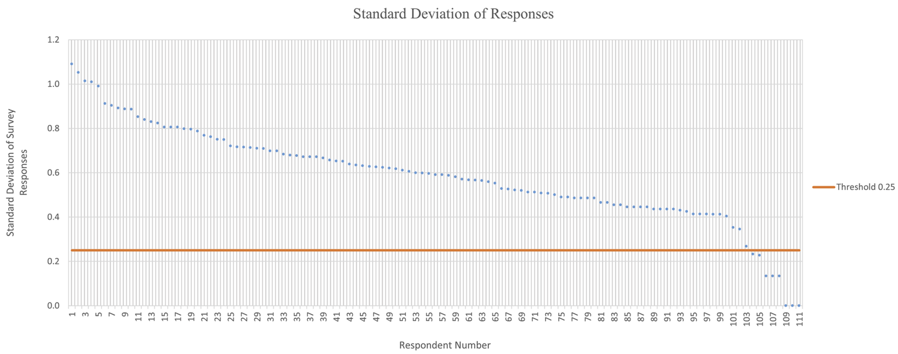

Figure 7. Standard deviation values per respondent in descending order. Source: Authors' own work

response behaviour across items, validating the dataset's suitability for subsequent latent structure analysis.

4.3.3 Impermissible Value Screening and range validation. Following the SD screening, a secondary validation step was performed to identify any impermissible values, specifically responses falling outside the designated five-point Likert scale range of 1 (Strongly Agree) to 5 (Strongly Disagree). While such anomalies are rare in established survey platforms like Qualtrics, they can occasionally occur due to data entry errors, system glitches, or participant interference. If uncorrected, these values may distort statistical outputs and compromise the integrity of psychometric analysis (Hair *et al*., 2010; Byrne, 2016).

This screening was conducted on the final dataset of 103 valid responses, retained after applying the SD threshold described earlier. All 55 competency items were examined using SPSS descriptive and frequency analyses to ensure compliance with the valid scale boundaries. No impermissible entries (values below 1 or above 5) were identified, confirming dataset integrity.

A small number of items recorded maximum scores below 5 (e.g. 3 or 4), which were interpreted as natural variations in response distribution rather than anomalies, indicating that no respondents rated those competencies at the lowest level of agreement. These results confirm that the dataset met all scale validity requirements. A complete summary of this screening process is provided in Appendix 1 (Table A1).

4.3.4 Skewness and kurtosis analysis. To confirm the dataset's suitability for factor-based statistical techniques, particularly PAF for EFA, skewness and kurtosis values were calculated for all 55 competency items. These measures describe the symmetry (skewness) and peakiness or tailedness (kurtosis) of each item's response distribution. Ensuring acceptable ranges for these values is essential in psychometric research, as substantial non-normality can distort inter-item correlations and bias model estimation (Hair *et al*., 2010; Byrne, 2016; Kline, 2023).

While the ideal normality range is often cited as $\pm$1.0, for ordinal Likert-type data a more flexible criterion of $\pm$2.0 is widely accepted as sufficient for EFA and SEM without requiring transformation (West *et al*., 1995; DeCarlo, 1997; Finney and DiStefano, 2006; Kyriazos, 2018).

The SPSS results showed that skewness values ranged from 0.022 (S21) to 1.324 (CP6), and kurtosis values ranged from $-$1.369 (K8) to 2.334 (CP6). Most items were well within the recommended $\pm$2.0 threshold. One item, CP6, slightly exceeded the kurtosis threshold, likely reflecting strong consensus among respondents regarding its importance. This minor deviation was not considered problematic and did not warrant data transformation. All items were therefore retained for subsequent EFA. A detailed summary of skewness and kurtosis statistics is provided in Appendix 2 (Table A2).

4.4 Phase two outcome: participant demographics and sample characteristics

This section presents the demographic and professional characteristics of the survey participants, focussing on the final subset of 103 respondents whose data were retained for EFA within the SEM process. These respondents satisfied the inclusion criteria outlined in Section 3.2 and met the psychometric adequacy conditions described in Section 4.3, including minimum SD thresholds, valid response ranges, and acceptable skewness and kurtosis parameters.

In total, 540 survey invitations were distributed, from which 111 responses were received, representing a gross response rate of 20.6%. After data cleaning and quality screening, 103 valid responses were retained, resulting in a usable response rate of 19.1%. This rate aligns with established benchmarks for organisational surveys (Baruch and Holtom, 2008).

All retained participants met the purposive sampling requirements of having at least five years of professional experience in AEC-related disciplines and active involvement in digitally mediated project delivery. This ensured a dataset reflecting professional maturity and domain-specific expertise (Palinkas *et al*., 2015; Etikan *et al*., 2016).

As shown in Figure 8, the age profile of respondents was weighted toward mid-career professionals: 30–39 years (55%), 40–49 years (25%), 20–29 years (13%), and 50 years and over (7%). No respondents were under the age of 20, confirming a professionally mature sample.

The gender distribution of respondents is shown in Figure 9. A total of 76 participants (74%) identified as male, 26 (25%) identified as female, and one respondent (1%) selected "prefer not to say." No participants identified as non-binary or third gender.

All participants reported more than five years of industry experience. As shown in Figure 10, the largest subgroup (35%) had 5–10 years of experience, followed by 10–15 years (28%), 15–20 years (17%), and over 20 years (19%). This confirms the professional maturity of the sample.

The most represented professional field was Digital and Technology roles, including BIM/VDC specialists, digital engineers, and data analysts, accounting for 34% of respondents. This

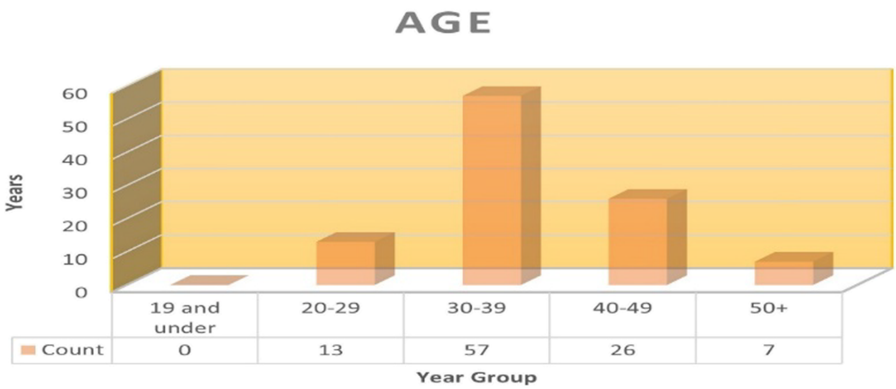

Figure 8. Age distribution of survey participants. Source: Authors' own work

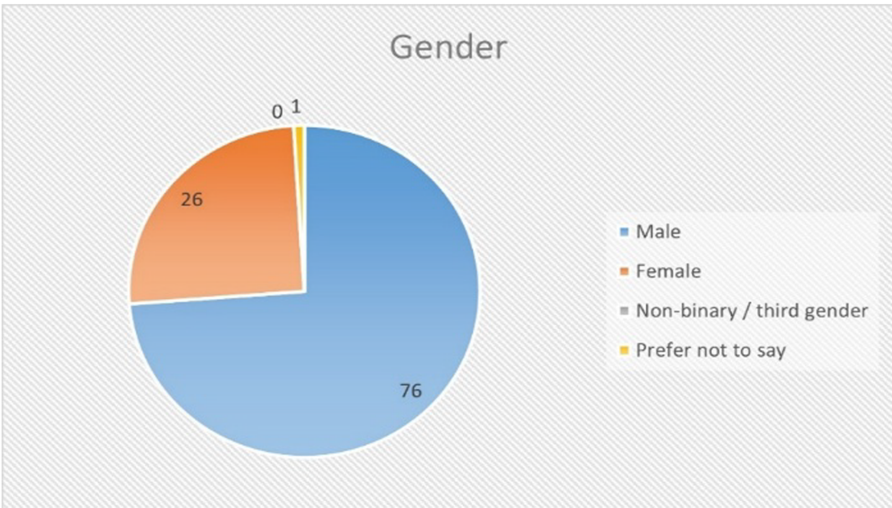

Figure 9. Gender distribution of survey participants. Source: Authors' own work

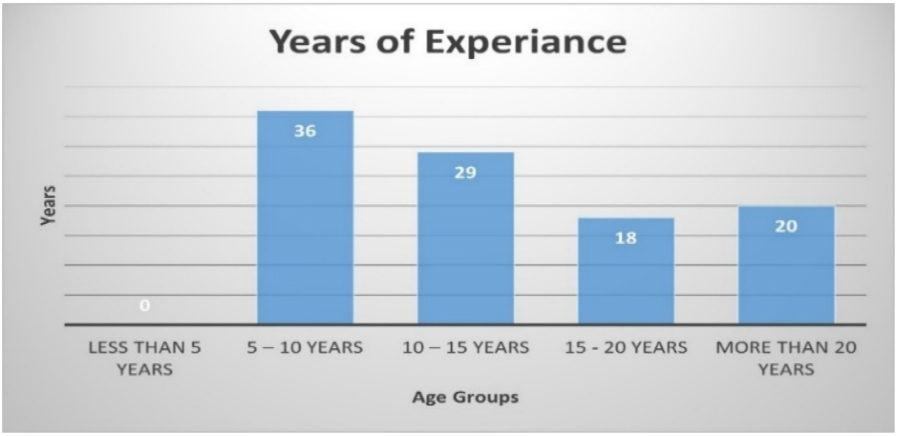

Figure 10. Years of experience among respondents. Source: Authors’ own work

was followed by Project Management (24%), Construction Engineering (17%), and Design and Architecture (9%). A further 16% selected “Other,” representing multidisciplinary roles such as sustainability, academia, or asset management, as shown in Figure 11.

Respondents also represented a range of organisational positions. As illustrated in Figure 12, 38% were classified as “Other” (consultants, academics, and specialists), followed by Managers (30%), Senior Managers (18%), Directors (11%), and Quantity Surveyors (3%). This mix of strategic and operational positions supports a balanced evaluation of competencies across project delivery levels.

Educational attainment was consistently high. As shown in Figure 13, 44% of participants held a Master’s degree, 34% a Bachelor’s, and 13% a PhD. The remaining participants held Diplomas (3%) or other qualifications (7%), including postgraduate certificates and industry training. This reflects the increasingly knowledge-intensive nature of digital leadership roles in construction.

Figure 11. Professional field distribution. Source: Authors’ own work

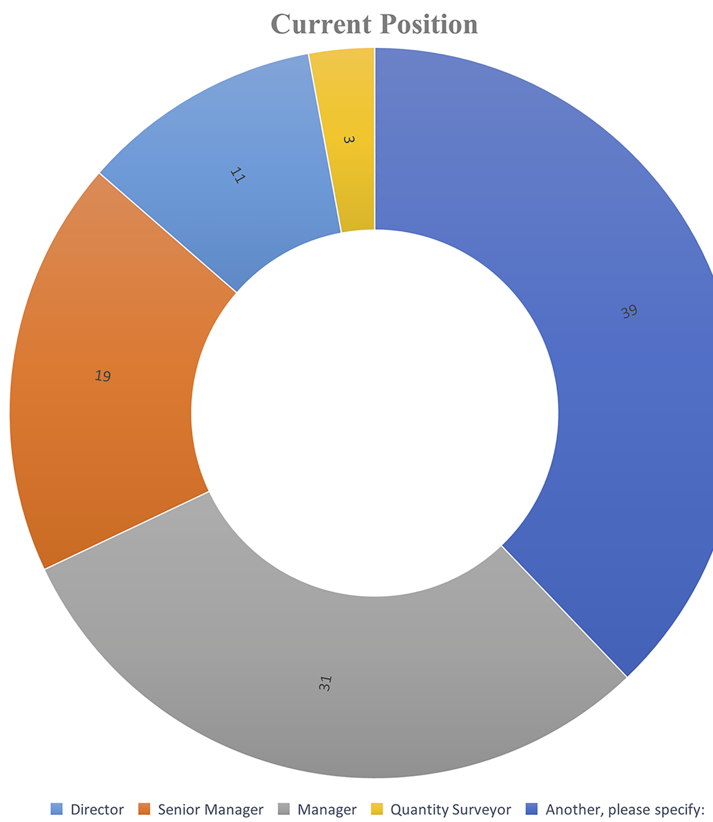

Figure 12. Current position of respondents. Source: Authors’ own work

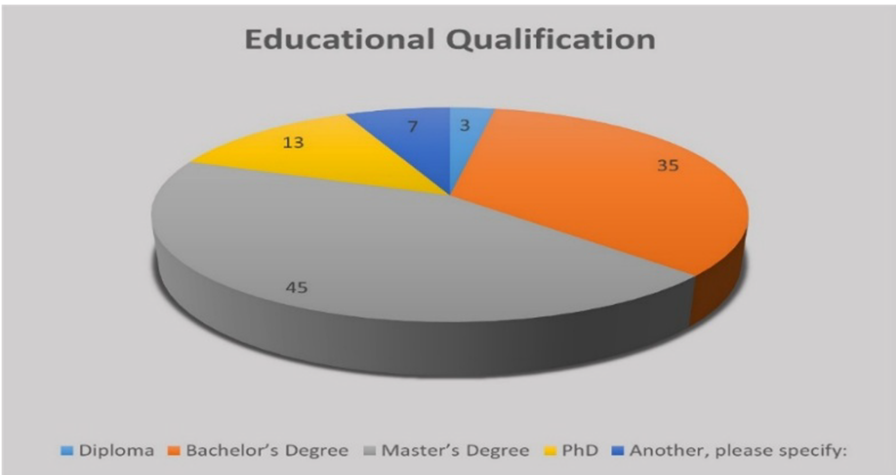

Figure 13. Educational background of respondents. Source: Authors’ own work

Participants also demonstrated strong familiarity with digital technologies. As presented in Figure 14, 36% identified as very familiar with digital construction tools, 46% as familiar, 17% as moderately familiar, and only 1% as not familiar. This indicates a digitally proficient sample well-positioned to evaluate the competency framework.

In summary, the final dataset comprises 103 qualified, digitally engaged professionals representing a diverse cross-section of the AEC sector across New Zealand and Australia. Their demographic and professional characteristics align closely with the study's target population, reinforcing the validity of the expert-based sampling strategy. Given the high degree of digital familiarity and breadth of experience across roles and disciplines, this sample provides a robust foundation for EFA. The following section presents the outcomes of the EFA conducted on this validated dataset.

5. Final EFA-derived competency framework for next-gen digital PMs

This section presents the final structural and visual representation of the empirically validated Next-Gen Digital PM Competency Framework. Based on the outcomes of the EFA, seven distinct latent factors were identified, each comprising statistically and conceptually coherent clusters of competencies. These groupings reflect the evolving demands of digital project environments and consolidate the essential capabilities required for PMs operating in technology-integrated construction settings.

Each factor was thematically interpreted and named according to the shared intent, functional application, and behavioural or knowledge-based characteristics of its underlying competencies. Collectively, the seven latent constructs form a holistic framework that aligns with the theoretical foundation established earlier in this study, encompassing the three competency domains of Skills, Knowledge, and Core Personality Traits.

The final empirically derived factors comprise (1) Digital Execution and Optimisation, which integrates competencies related to project control, automation, and performance enhancement; (2) Human-Centred Digital Leadership, which emphasises behavioural, emotional, and collaborative capacities in digitally mediated teams; (3) Lifecycle Risk and Compliance Knowledge, which encompasses governance, safety, and contractual oversight within digital processes; (4) Digital Sustainability Intelligence, which focuses on environmentally responsible strategies and carbon-conscious digital practices; (5) Digital

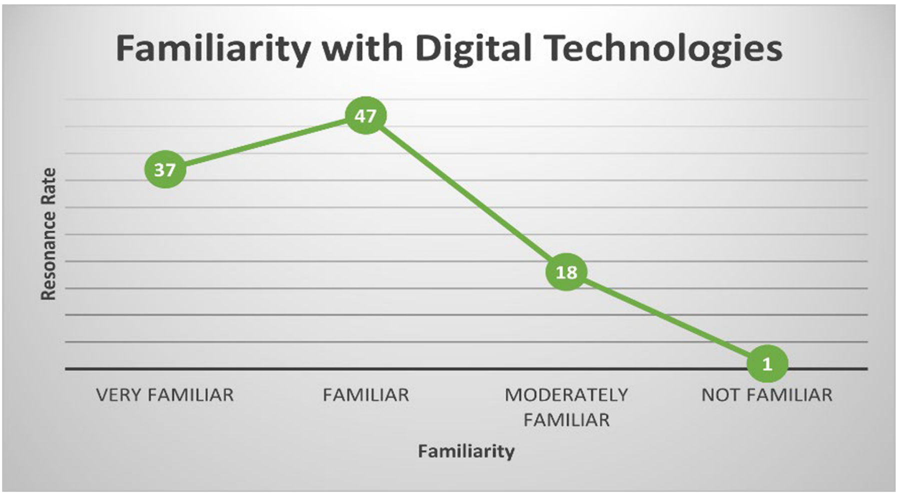

Figure 14. Familiarity with digital construction technologies. Source: Authors' own work

Tools Proficiency and Automation, which reflects operational fluency in advanced digital systems and platforms; (6) Digital Content and Data Management, which ensures the integrity, analytics, and creative reuse of project data; and (7) Digital Transformation Enablement Skills, which advances innovation, communication, and upskilling in adaptive project contexts.

To enhance clarity and usability, a radial cluster diagram was developed to illustrate the framework's internal structure. As shown in Figure 15, each latent factor is positioned as a node surrounding the central framework, with its associated competencies branching outward. This visualisation offers a high-level overview of the competency architecture and provides an intuitive understanding of how specific digital capabilities are organised within broader thematic domains.

This visual framework summarises the EFA findings and provides the conceptual foundation for confirmatory validation. It captures the multidimensional nature of digital PM competencies, integrating behavioural leadership, technical proficiency, innovation capability, and sustainability intelligence into a unified structure. As an empirically grounded framework, it offers a robust, data-driven basis for confirmatory testing through CFA and for wider application across diverse digital-construction contexts.

6. Practical implications for digital project management practice

This study provides construction PMs with an empirically validated digital competency framework that clarifies the human capabilities required to manage digitally enabled construction projects. Rather than focussing on specific technologies, the seven-factor model articulates role-based digital PM competencies spanning execution, leadership, governance, sustainability, automation, data management, and transformation enablement.

From the industry perspective, the framework supports several practical applications.

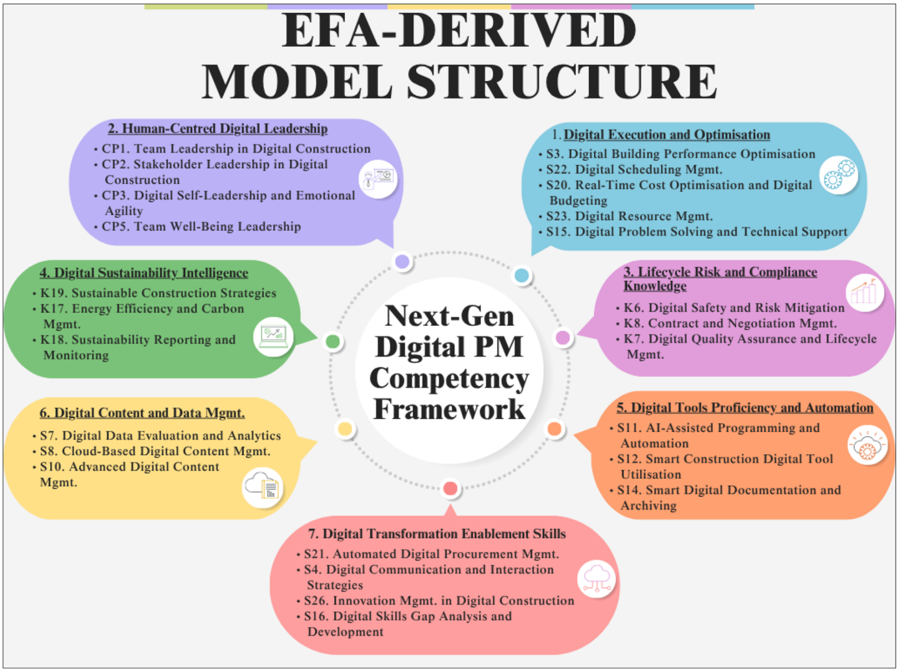

Figure 15. Next-gen digital PM competency framework: EFA-derived model structure. Source: Authors' own work

(1) *Competency assessment and benchmarking (diagnostic):* PMs can use the seven competency domains to evaluate and benchmark their current digital capability profile against empirically derived standards, enabling evidence-based assessment of professional readiness for digitally intensive projects.

(2) *Targeted training and upskilling (developmental):* Based on identified capability gaps, the framework supports the design of targeted professional development and upskilling pathways aligned with the specific digital demands of construction project delivery.

(3) *Project role alignment and capability planning (allocation):* At the organisational level, firms can align PMs to projects based on demonstrated digital competency profiles, improving role project fit and reducing delivery risk in complex digital environments.

(4) *Digital project delivery support (operational):* During project execution, the framework informs early decisions on capability support, such as mentoring, specialist input, or supplementary training, where specific digital competencies are critical to project success.

For example, in a digitally enabled construction project requiring advanced data integration and automation, a PM's competency profile may indicate greater emphasis on execution-oriented capabilities (e.g. Digital Execution and Optimisation) relative to data-centric competencies (e.g. Digital Content and Data Management). Applying the framework enables early identification of such capability distributions, informing targeted professional development, role support, or team-level capability balancing. This supports improved coordination, data reliability, and decision-making throughout the project lifecycle.

Overall, the framework serves as a practical competency reference for PMs, supporting systematic capability development and more effective leadership of digital construction projects.

7. Limitations and future research

While this study presents a validated and empirically grounded framework for Next-Gen Digital PM Competencies, several limitations must be acknowledged to ensure transparency and contextual accuracy. The scope of the investigation was shaped by a purposive sampling strategy focused on professionals within a defined regional and industry context. Consequently, the generalisability of the findings may be constrained across different geographic, cultural, or sectoral settings. Although the competencies reflect current digital practices in construction, they may not fully capture variations in digital maturity or project delivery approaches across other global contexts.

From a methodological perspective, the study employed a single-phase EFA to derive the underlying structure of digital PM competencies. While EFA provides a robust exploratory basis for identifying latent constructs, it does not establish model fit or confirm predictive validity. Accordingly, the present results should be viewed as an empirically supported framework that warrants subsequent confirmatory testing. Future research using CFA can strengthen the framework's statistical validity by assessing goodness-of-fit indices, internal consistency, and discriminant validity. Although the sample size achieved was suitable for EFA, future studies involving larger and more diverse participant groups would enhance statistical power and enable comparative analysis across roles, domains, and regional contexts.

Another limitation concerns the exclusion of 30 competencies during the EFA refinement phase. While their removal was necessary to achieve structural clarity, parsimony, and discriminant validity, these competencies remain theoretically meaningful. Their exclusion narrows the immediate scope of the validated framework but does not diminish their relevance to specialised or emerging areas such as cybersecurity, AI integration, and professional development. Subsequent studies may reintroduce or re-examine these elements in extended frameworks, role-specific models, or through complementary qualitative methods such as Delphi studies, ensuring comprehensive coverage of digital PM capabilities.

Looking forward, multiple pathways exist for expanding and validating the proposed framework. Cross-country and cross-sector replication could test its adaptability under diverse socio-economic, cultural, and regulatory conditions. Longitudinal investigations could trace the evolution of digital PM competencies over time and their influence on project outcomes within dynamic organisational contexts. Moreover, as digital transformation continues to advance, new competencies are likely to emerge. Extending the framework through continuous empirical refinement will ensure that it remains responsive to the evolving demands of digital construction and leadership practice.

By acknowledging these limitations and identifying avenues for further inquiry, this study positions the EFA-derived framework as a robust empirical foundation for ongoing model refinement and theoretical advancement. Rather than representing a conclusive construct, it offers a statistically grounded, adaptable platform for confirmatory validation and future research on digital project management competencies in the built environment.

8. Conclusion

This study has presented the results of the Exploratory Factor Analysis (EFA), culminating in the development of an empirically grounded framework for Next-Gen Digital Project Manager (PM) competencies. Through a systematic, multi-stage process, 55 validated competency items were evaluated for both statistical adequacy and theoretical coherence. The analysis produced a seven-factor solution comprising 25 retained competencies, which were statistically grouped into coherent thematic clusters aligned with the conceptual framework established earlier in this research.

The seven empirically derived factors, Digital Execution and Optimisation, Human-Centred Digital Leadership, Lifecycle Risk and Compliance Knowledge, Digital Sustainability Intelligence, Digital Tools Proficiency and Automation, Digital Content and Data Management, and Digital Transformation Enablement Skills, represent the multidimensional domains required for PMs to lead effectively in digitally transformed construction environments. Together, these clusters highlight the balance between technical fluency, behavioural leadership, and cognitive oversight essential for navigating the complexity of data-driven, technology-integrated project delivery.

By empirically identifying the latent structure of digital PM competencies, this study validates and extends the theoretical foundations established earlier while enhancing practical applicability. Weak, redundant, or ambiguous items were systematically removed to ensure parsimony without compromising conceptual integrity. The application of Principal Axis Factoring (PAF) with Promax rotation, supported by eigenvalue thresholds, scree plot interpretation, and thematic coherence, yielded a statistically robust and theoretically consistent seven-factor solution.

Theoretically, this study contributes by empirically validating the latent structure of Next-Gen Digital PM competencies in construction, moving beyond conceptual classifications to establish a statistically grounded framework integrating skills, knowledge, and core personality traits for digitally transformed project environments. Practically, the validated seven-factor framework offers an evidence-based reference for competency assessment and benchmarking, targeted workforce development and upskilling, project role alignment and capability planning, and digital project delivery support, supporting construction PMs and organisations in leading digitally enabled projects more effectively.

In future applications, the framework may inform the design of construction industry training programmes, support competency-based professional certification, and guide organisational digital transformation strategies within Architecture, Engineering, and

Construction (AEC) firms, including capability planning, role alignment, and targeted professional development across digitally enabled construction projects.

The EFA outcomes are consolidated in a visual representation of the competency framework, Figure 15, offering a clear and accessible map of the latent constructs underpinning digital PM competency. This framework advances both academic understanding and professional application by providing an evidence-based foundation for developing digital leadership and competency assessment models within the construction sector.

Looking ahead, this empirically derived framework provides a statistically grounded foundation for confirmatory testing through Confirmatory Factor Analysis (CFA) within a Structural Equation Modelling (SEM) framework. This next phase will evaluate model fit, reliability, and validity using the same dataset to confirm the internal structure of the framework, while future research may expand validation across broader and more diverse samples. This progression advances the research trajectory from exploratory identification to the development of a theoretically robust and empirically validated Next-Gen Digital PM Competency Model for the digitally transformed built environment.

Acknowledgments

The authors acknowledge the support of the Auckland University of Technology (AUT) and thank all industry professionals who participated in the survey. Ethical approval for this study involving human participants was granted by the Auckland University of Technology Ethics Committee (AUTEC), approval reference 23/257. AI-assisted language refinement: AI-based language assistance tools were used solely to improve language clarity, grammar, and readability. These tools were not used for draughting the manuscript, data analysis, interpretation of results, or the generation of original scholarly content. All conceptual development, methodological decisions, and analytical interpretations were undertaken entirely by the authors.

(The Appendix follows overleaf)

Appendix 1
Impermissible value screening

Table A1. Descriptive statistics for impermissible value screening

Descriptive statistics	*N*	Minimum	Maximum
S1	103	1	4
S2	103	1	3
S3	103	1	4
S4	103	1	4
S5	103	1	4
S6	103	1	3
S7	103	1	3
S8	103	1	3
S9	103	1	4
S10	103	1	4
S11	103	1	4
S12	103	1	3
S13	103	1	3
S14	103	1	4
S15	103	1	4
S16	103	1	5
S17	103	1	4
S18	103	1	4
S19	103	1	3
S20	103	1	3
S21	103	1	3
S22	103	1	4
S23	103	1	4
S24	103	1	4
S25	103	1	4
S26	103	1	4
K1	103	1	3
K2	103	1	5
K3	103	1	4
K4	103	1	3
K5	103	1	3
K6	103	1	4
K7	103	1	3
K8	103	1	3
K9	103	1	3
K10	103	1	3
K11	103	1	4
K12	103	1	3
K13	103	1	3
K14	103	1	3
K15	103	1	4
K16	103	1	4
K17	103	1	4
K18	103	1	4
K19	103	1	4
K20	103	1	5
K21	103	1	5
CP1	103	1	4
CP2	103	1	3

(*continued*)

Table A1. Continued

Descriptive statistics	*N*	Minimum	Maximum
CP3	103	1	4
CP4	103	1	3
CP5	103	1	3
CP6	103	1	4
CP7	103	1	4
CP8	103	1	5
Valid N (listwise)	103		

Source(s): Authors' own work

Appendix 2
Skewness and Kurtosis screening

Table A2. Descriptive statistics for skewness and kurtosis screening

Descriptive statistics	*N* Statistic	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
S1	103	0.597	0.238	−0.207	0.472
S2	103	0.294	0.238	−0.779	0.472
S3	103	0.346	0.238	−0.369	0.472
S4	103	0.770	0.238	−0.093	0.472
S5	103	1.006	0.238	0.861	0.472
S6	103	0.589	0.238	−0.639	0.472
S7	103	0.844	0.238	−0.281	0.472
S8	103	0.422	0.238	−0.869	0.472
S9	103	0.936	0.238	0.378	0.472
S10	103	0.808	0.238	1.005	0.472
S11	103	0.320	0.238	−0.733	0.472
S12	103	0.435	0.238	−0.754	0.472
S13	103	0.640	0.238	−0.571	0.472
S14	103	0.735	0.238	0.241	0.472
S15	103	0.742	0.238	0.378	0.472
S16	103	1.029	0.238	2.263	0.472
S17	103	0.609	0.238	−0.335	0.472
S18	103	0.482	0.238	−0.233	0.472
S19	103	0.140	0.238	−0.970	0.472
S20	103	0.147	0.238	−1.222	0.472
S21	103	0.022	0.238	−0.737	0.472
S22	103	0.445	0.238	−0.181	0.472
S23	103	0.636	0.238	0.358	0.472
S24	103	0.469	0.238	−0.311	0.472
S25	103	0.655	0.238	−0.112	0.472
S26	103	0.280	0.238	−0.778	0.472
K1	103	0.627	0.238	−0.749	0.472
K2	103	0.538	0.238	0.308	0.472
K3	103	0.273	0.238	−0.049	0.472
K4	103	0.167	0.238	−0.537	0.472
K5	103	0.341	0.238	−0.860	0.472

(*continued*)

Table A2. Continued

Descriptive statistics	*N* Statistic	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
K6	103	0.388	0.238	−0.640	0.472
K7	103	0.267	0.238	−0.907	0.472
K8	103	0.052	0.238	−1.369	0.472
K9	103	0.167	0.238	−0.537	0.472
K10	103	0.620	0.238	−0.621	0.472
K11	103	0.682	0.238	0.776	0.472
K12	103	0.449	0.238	−0.993	0.472
K13	103	0.364	0.238	−0.872	0.472
K14	103	0.234	0.238	−0.983	0.472
K15	103	0.398	0.238	−0.216	0.472
K16	103	0.591	0.238	0.529	0.472
K17	103	0.353	0.238	−0.358	0.472
K18	103	0.522	0.238	−0.123	0.472
K19	103	0.649	0.238	0.060	0.472
K20	103	0.946	0.238	1.255	0.472
K21	103	0.537	0.238	0.223	0.472
CP1	103	0.823	0.238	0.409	0.472
CP2	103	0.560	0.238	−0.654	0.472
CP3	103	0.548	0.238	−0.391	0.472
CP4	103	0.560	0.238	−0.654	0.472
CP5	103	0.650	0.238	−0.600	0.472
CP6	103	1.324	0.238	2.334	0.472
CP7	103	0.909	0.238	0.484	0.472
CP8	103	0.773	0.238	0.970	0.472
Valid N (listwise)	103				

Source(s): Authors' own work

Appendix 3
KMO and Bartlett's test results

Table A3. KMO and Bartlett's test results

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.736
Bartlett's Test of Sphericity	Approx. Chi-Square	3579.238
	df	1,485
	Sig.	<0.001

Communalities	Initial	Extraction
S1	0.761	0.665
S2	0.846	0.822
S3	0.765	0.648

(*continued*)

Table A3. Continued

Communalities	Initial	Extraction
S4	0.742	0.576
S5	0.839	0.640
S6	0.829	0.824
S7	0.727	0.673
S8	0.758	0.580
S9	0.731	0.748
S10	0.568	0.517
S11	0.652	0.468
S12	0.711	0.679
S13	0.678	0.419
S14	0.791	0.663
S15	0.769	0.502
S16	0.718	0.506
S17	0.824	0.737
S18	0.813	0.705
S19	0.766	0.629
S20	0.773	0.654
S21	0.661	0.630
S22	0.790	0.657
S23	0.764	0.691
S24	0.784	0.626
S25	0.820	0.630
S26	0.818	0.700
K1	0.703	0.621
K2	0.786	0.663
K3	0.775	0.581
K4	0.732	0.732
K5	0.775	0.710
K6	0.782	0.726
K7	0.822	0.698
K8	0.823	0.817
K9	0.678	0.437
K10	0.655	0.472
K11	0.720	0.558
K12	0.728	0.639
K13	0.764	0.667
K14	0.777	0.726
K15	0.804	0.621
K16	0.686	0.499
K17	0.791	0.633
K18	0.874	0.796
K19	0.859	0.681
K20	0.665	0.466
K21	0.587	0.358
CP1	0.746	0.681
CP2	0.675	0.572
CP3	0.785	0.629
CP4	0.809	0.766
CP5	0.715	0.613
CP6	0.805	0.815
CP7	0.760	0.600
CP8	0.734	0.615

Note(s): Extraction Method: Principal Axis Factoring
Source(s): Authors' own work

Appendix 4
Total variance explained – SPSS outcome

Table A4. Total variance explained results

Total variance explained

Initial eigenvalue				Extracted sums of squared loadings			Rotation sums of squared loading[a]
Factor	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total
1	14.506	26.375	26.375	14.157	25.739	25.739	9.494
2	3.996	7.265	33.640	3.648	6.633	32.372	5.403
3	3.170	5.763	39.404	2.808	5.105	37.478	6.033
4	2.438	4.433	43.837	2.078	3.779	41.257	8.968
5	2.335	4.245	48.081	1.989	3.616	44.873	6.966
6	2.104	3.825	51.906	1.759	3.198	48.071	3.816
7	1.696	3.083	54.989	1.330	2.418	50.489	4.036
8	1.521	2.766	57.755	1.155	2.100	52.588	5.691
9	1.421	2.583	60.338	1.074	1.953	54.541	4.092
10	1.405	2.554	62.892	1.045	1.901	56.442	7.124
11	1.246	2.265	65.157	0.910	1.655	58.097	3.922
12	1.193	2.169	67.326	0.838	1.523	59.620	2.144
13	1.153	2.097	69.422	0.801	1.456	61.077	4.216
14	1.081	1.965	71.388	0.723	1.314	62.391	4.560
15	1.017	1.849	73.237	0.663	1.206	63.597	0.949
16	0.964	1.753	74.990				
17	0.919	1.672	76.662				
18	0.882	1.604	78.266				
19	0.804	1.463	79.728				
20	0.782	1.422	81.151				
21	0.705	1.283	82.433				
22	0.692	1.259	83.692				
23	0.642	1.168	84.860				
24	0.600	1.091	85.951				
25	0.584	1.062	87.013				
26	0.544	0.989	88.002				
27	0.540	0.981	88.983				
28	0.475	0.864	89.847				
29	0.438	0.796	90.644				
30	0.420	0.764	91.408				
31	0.405	0.737	92.145				
32	0.396	0.719	92.864				
33	0.332	0.603	93.467				
34	0.320	0.583	94.050				
35	0.299	0.544	94.594				
36	0.285	0.518	95.112				
37	0.268	0.488	95.600				
38	0.251	0.456	96.057				
39	0.236	0.430	96.486				
40	0.224	0.408	96.894				
41	0.209	0.380	97.274				
42	0.190	0.346	97.620				
43	0.175	0.318	97.938				
44	0.166	0.302	98.240				
45	0.149	0.271	98.511				

(*continued*)

Table A4. Continued

Total variance explained							
Initial eigenvalue				Extracted sums of squared loadings			Rotation sums of squared loading[a]
Factor	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total
46	0.127	0.231	98.743				
47	0.111	0.201	98.944				
48	0.104	0.190	99.134				
49	0.101	0.183	99.317				
50	0.085	0.154	99.471				
51	0.084	0.153	99.624				
52	0.073	0.132	99.756				
53	0.056	0.102	99.858				
54	0.044	0.079	9.937				
55	0.034	0.063	100.000				

Note(s): Extraction Method: Principal Axis Factoring, [a]When factors are correlated, sums of squared loadings cannot be added to obtain a total variance

Source(s): Authors' own work

Appendix 5
Communalities of extracted factors

Table A5. Communalities of extracted factors

Communalities	Initial	Extraction
S1	0.761	0.619
S2	0.846	0.578
S3	0.765	0.564
S4	0.742	0.478
S5	0.839	0.540
S6	0.829	0.372
S7	0.727	0.322
S8	0.758	0.583
S9	0.731	0.473
S10	0.568	0.419
S11	0.652	0.334
S12	0.711	0.491
S13	0.678	0.292
S14	0.791	0.455
S15	0.769	0.434
S16	0.718	0.455
S17	0.824	0.549
S18	0.813	0.416
S19	0.766	0.613
S20	0.773	0.602
S21	0.661	0.296
S22	0.790	0.573

(*continued*)

Table A5. Continued

Communalities	Initial	Extraction
S23	0.764	0.344
S24	0.784	0.599
S25	0.820	0.599
S26	0.818	0.596
K1	0.703	0.438
K2	0.786	0.503
K3	0.775	0.498
K4	0.732	0.435
K5	0.775	0.538
K6	0.782	0.450
K7	0.822	0.591
K8	0.823	0.612
K9	0.678	0.343
K10	0.655	0.290
K11	0.720	0.386
K12	0.728	0.422
K13	0.764	0.448
K14	0.777	0.624
K15	0.804	0.542
K16	0.686	0.357
K17	0.791	0.502
K18	0.874	0.628
K19	0.859	0.630
K20	0.665	0.337
K21	0.587	0.264
CP1	0.746	0.521
CP2	0.675	0.482
CP3	0.785	0.511
CP4	0.809	0.681
CP5	0.715	0.542
CP6	0.805	0.505
CP7	0.760	0.520
CP8	0.734	0.570

Note(s): Extraction Method: Principal Axis Factoring
Source(s): Authors' own work

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