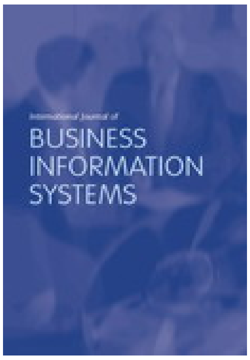

International Journal of Business Information Systems

ISSN online: 1746-0980 - ISSN print: 1746-0972
https://www.inderscience.com/ijbis

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DOI: 10.1504/IJBIS.2026.10080114

Article History:

Received:	17 May 2026
Last revised:	20 June 2026
Accepted:	20 June 2026
Published online:	05 August 2026

Developing and operationalising a sector-specific big data maturity model for the telecommunications industry

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Abstract: Despite the growing strategic importance of big data in the telecommunications industry, existing big data maturity models remain largely generic and insufficiently adapted to sector-specific operational and analytical requirements. This study aims to refine and operationalise a sector-specific big data maturity model for telecommunications. Grounded in design science research and a mixed-methods approach, the study involved 50 experts from academia and industry through iterative qualitative and quantitative evaluation. The findings identified strong consensus regarding the importance of data governance, business development, and network performance, while qualitative feedback emphasised simplification, terminology standardisation, and the integration of emerging capabilities such as artificial intelligence. The operationalisation process resulted in a combined evaluative structure, a five-level maturity framework, and weighted dimensions and sub-dimensions. The final model consists of seven dimensions and 28 sub-dimensions. The proposed framework supports maturity assessment, capability gap identification, and strategic digital transformation within telecommunications organisations

Keywords: big data maturity model; BDMM; telecommunications industry; big data analytics; digital transformation; maturity assessment; strategic performance; data-driven decision making.

Reference to this paper should be made as follows: Desku, F. and Besimi, A. (2026) 'Developing and operationalising a sector-specific big data maturity model for the telecommunications industry', *Int. J. Business Information Systems*, Vol. 52, No. 7, pp.1–27.

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1 Introduction

Big data maturity models (BDMMs) are structured frameworks designed to evaluate how effectively organisations manage, analyse, and utilise data to support decision-making and strategic objectives (Comuzzi and Patel, 2016; Turetken and Van Looy, 2024). These models typically define a set of dimensions, such as data governance, technology, analytics capabilities, and organisational culture, and assess them across progressive maturity levels, ranging from basic or ad hoc practices to highly advanced, data-driven operations (Al-Sai et al., 2022). In addition, BDMMs serve as practical tools for guiding organisational transformation toward more advanced data usage and they play "a transformative role in modern business intelligence" (Udeh et al., 2024). They enable organisations to identify gaps, prioritise investments, and develop structured roadmaps for improvement, ultimately enhancing performance and competitive advantage (Dubey et al., 2019). By positioning organisations within these levels, maturity models provide a clear understanding of current capabilities and highlight areas that require improvement (Wendler, 2012; Langer, 2025; Müller-Stein et al., 2025).

Despite the growing number of BDMMs proposed in the literature, significant conceptual and practical challenges remain unresolved. Existing models vary considerably in their dimensions, maturity structures, and assessment approaches, resulting in fragmented conceptualisations of big data maturity and limited comparability across frameworks (Al-Sai et al., 2022; Mouhib et al., 2020). While many models provide broad organisational guidance, they often remain highly generic and insufficiently sensitive to the operational realities, technological architectures, and strategic priorities of specific industries. Generic maturity models often assume that organisations evolve through relatively uniform maturity pathways, emphasising common capabilities such as leadership, organisational structure, technology, and human capital across industries (Saravanabhavan et al., 2024). However, this assumption may oversimplify the complexity of highly data-intensive sectors such as telecommunications, where organisations operate within dynamic environments characterised by real-time data streams, distributed infrastructures, network virtualisation, AI-driven optimisation, and continuously evolving customer and service ecosystems.

In the telecommunications industry, operators generate and manage vast and complex datasets derived from network activity, customer interactions, and service usage (Alshawawreh et al., 2024; Kastouni and Ait Lahcen, 2022). These data enable a wide range of telecom applications, including network optimisation, customer experience enhancement, churn prediction, fraud detection, product development, and strategic decision-making (Chen et al., 2014). The evolution of mobile communication technologies has further intensified the role of data analytics in this sector, progressing from basic operational reporting in earlier network generations to advanced behavioural and strategic analytics in 4G, 5G, and beyond (Kastouni and Ait Lahcen, 2022). In this sector, big data is not limited to business intelligence and reporting functions but is deeply embedded in core operational processes, including network management, predictive maintenance, traffic optimisation, fraud detection, customer behaviour analysis, and autonomous decision-making systems (Lottu and Ezeigweneme, 2024). Consequently, generic maturity frameworks may inadequately capture the interdependence between technological infrastructure, advanced analytics, operational responsiveness, and strategic automation that characterise modern telecom ecosystems.

Furthermore, many existing maturity models remain conceptual in nature, offering high-level capability dimensions without sufficiently operationalising how maturity should be measured, weighted, interpreted, or translated into actionable organisational assessment mechanisms. This limits their practical applicability and reduces their value for organisations seeking systematic evaluation and benchmarking of Big Data capabilities. Another limitation of generic maturity frameworks lies in their relatively static representation of organisational development. In rapidly evolving digital environments such as telecommunications, Big Data maturity is not a linear or purely technological progression, but rather a dynamic interaction between organisational capabilities, governance structures, AI integration, strategic adaptability, and ecosystem responsiveness.

This study focuses on the refinement and operationalisation of a sector-specific BDMM tailored for the telecommunications industry. The process of developing the BDMM for the telecommunications industry was organised into three main phases as follows:

1 development of the core framework
2 refinement of the model
3 definition of the maturity scale.

Following the initial development of the core framework, conducted by Desku and Besimi (2025). Phase 2 is focused on the refinement and finalisation of the model ensuring that the proposed framework, including dimensions and sub-dimensions are in line with the specific requirements of the telecommunication industry. Subsequently, phase 3 addresses the operationalisation of the model by developing mechanisms that enable its practical use. In line with the role of maturity models as structured frameworks for assessing and improving organisational capabilities (Al-Sai et al., 2022), this phase strengthens the validity and relevance of the model for practical application. This includes the integration of the refined model into a structured assessment approach, allowing telecommunications organisations to evaluate their big data maturity, identify gaps, and receive actionable recommendations. By bridging the gap between theoretical development and real-world application, this approach supports organisations in enhancing their big data capabilities and progressing toward more automated, autonomous, and optimised operations, ultimately contributing to improved strategic performance (Horick, 2020).

2 Theoretical background

Resource-based theory (RBT) provides a strong theoretical foundation for understanding how organisations achieve and sustain competitive advantage. Barney (1991) argues that firms attain superior performance by leveraging resources that are valuable, rare, inimitable, and non-substitutable. Extending this perspective, Teece et al. (1997) emphasise the importance of dynamic capabilities in enabling organisations to adapt and reconfigure resources in rapidly changing environments. In this context, growing attention has been directed toward intangible resources such as data and analytics capabilities, which are increasingly recognised as critical drivers of competitive advantage in data-driven environments (Badshah et al., 2024). Within this theoretical lens, big data can be conceptualised as a strategic resource that supports enhanced decision-making, innovation, and operational efficiency. When combined with appropriate technological infrastructure, skilled human capital, and effective management practices, big data analytics capabilities can transform organisational processes and significantly improve performance (Gupta and George, 2016; Mikalef et al., 2018). Prior research further indicates that organisations leveraging such capabilities are better positioned to optimise operations, predict customer behaviour, and respond effectively to dynamic market conditions, thereby strengthening their competitive advantage (Dubey et al., 2019). Recent empirical evidence from the telecommunications sector further supports this argument by demonstrating that big data analytics capabilities enhance firm performance through improved data integration and data-driven decision-making processes (Khan and Fatima, 2025). Big data analytics enhances organisational decision-making by enabling deeper pattern recognition, predictive insights, and improved strategic responsiveness in digitally transforming business environments (Mydyti and Kadriu, 2021). This perspective is particularly relevant for the telecommunications industry, where large volumes of real-time data are continuously generated from networks, services, and customer interactions (Chen et al., 2014; Kastouni and Ait Lahcen, 2022). Despite this, existing BDMMs remain either too general or insufficiently operationalised for telecom-specific applications, as highlighted in recent systematic reviews (Al-Sai et al., 2022; Langer, 2025). Prior research also emphasises that maturity models should be adapted to specific organisational contexts to ensure relevance and applicability (Becker et al., 2010; Pöppelbuß and Röglinger, 2011). Therefore, this study contributes to the literature by refining and operationalising a sector-specific BDMM tailored to telecommunications, aligning with the principles of RBT (Barney, 1991) while addressing a clear gap in existing research.

3 Literature review

BDMMs have been widely developed to assess how organisations manage, integrate, and use data, particularly in relation to key big data characteristics such as volume, velocity, variety, and value, which strongly influence information systems performance and business outcomes (Al-Zwaylif et al., 2026). Existing models differ in their conceptual structure, maturity dimensions, evaluative mechanisms, and maturity progression logic (Đukić and Luković, 2025; Korsten et al., 2025). Recent reviews highlight this diversity, with Al-Sai et al. (2022) identifying 15 BDMMs and Mouhib et al. (2020) emphasising substantial variation in model architecture, dimensions, and assessment approaches across the literature.

A central distinction within the literature concerns the variation between generic and sector-specific maturity models. Generic models attempt to provide universally applicable frameworks for assessing organisational data capabilities across industries (Langer, 2025). While this broad applicability might increase usability, it also has important conceptual limitations. Generic maturity models often assume that organisations evolve through relatively uniform maturity pathways, where technological infrastructure, governance structures, analytics capabilities, and organisational culture develop in predictable and transferable ways (Pöppelbuß and Röglinger, 2011). However, such assumptions may oversimplify the complexity of highly data-intensive environments in which operations differ substantially across sectors. As a result, generic models frequently lack contextual sensitivity and might have limitations in capturing the strategic and operational dynamics shaping Big Data maturity within specific industries.

These limitations become particularly evident within telecommunications environments, characterised by continuous real-time data generation, distributed infrastructures, network virtualisation, predictive automation, and AI-driven operational optimisation (Agiwal et al., 2016). In this context, Big Data capabilities are deeply used within core operational systems rather than functioning only as decision-support tools. Consequently, big data maturity in telecommunications extends beyond analytical capability alone and increasingly encompasses the organisation’s capacity to integrate governance, operational responsiveness, network performance, customer analytics, and adaptive technological infrastructures into coordinated data ecosystems, where robust data governance becomes essential for ensuring integration, interoperability, and strategic value creation (Khan and Fatima, 2025; Pörtner et al., 2025; Jebur et al., 2026). Generic maturity models rarely take into consideration these interdependencies adequately, as they tend to treat organisational capabilities as relatively static constructs rather than dynamic and operationally integrated systems.

In response to the limitations of generic approaches, several studies have proposed domain-specific maturity models tailored to particular industries. For example, Hausladen and Schosser (2020) developed a maturity model for the airline industry, Daraghmeh and Brown (2021) proposed a model for healthcare environments, Willetts and Atkins (2024) introduced a big data analytics maturity model for small and medium enterprises (SMEs), while Fornasiero et al. (2024) examined AI and big data readiness in the process industry. Collectively, these studies indicate that generic maturity models often fail to capture sector-specific technological inter-dependencies, reinforcing the need for context-sensitive assessment frameworks.

This limitation is also evident within telecommunications-specific research. Keshavarz et al. (2021) proposed a capability-oriented framework incorporating dimensions such as technology, management, talent, domain knowledge, and innovation. While the framework represents an important step toward sector-sensitive big data assessment, it primarily focuses on identifying organisational capabilities rather than operationalising maturity as a progressive developmental construct. The absence of clearly defined maturity levels, evaluative structures, weighting mechanisms, and maturity granularity limits the framework’s ability to support organisational positioning, benchmarking, and longitudinal capability assessment. More importantly, the model conceptualises big data capabilities primarily as organisational resources rather than as dynamically evolving and interdependent operational systems embedded within telecommunications ecosystems.

The literature reveals an important conceptual and practical gap. Existing BDMMs remain either overly generic and insufficiently sensitive to telecommunications complexity or sector-specific but insufficiently operationalised for practical maturity assessment and strategic capability development. Furthermore, much of the existing literature continues to conceptualise maturity as a relatively linear and technology-centred progression, despite the increasingly adaptive, AI-driven, and ecosystem-dependent nature of contemporary telecommunications environments. These limitations highlight the need for a sector-specific and operationalised BDMM capable of integrating technological, operational, governance, strategic, and innovation-oriented capabilities within a coherent maturity assessment framework tailored to the telecommunications industry. In contrast, the model proposed in this study extends beyond capability identification by providing a fully operationalised maturity framework.

3.1 Frameworks informing the development of BDMMs

Existing maturity model development frameworks provide important methodological foundations for designing and operationalising organisational capability assessments; however, they differ considerably in their theoretical orientation, level of procedural detail, and emphasis on practical applicability. Among the most influential approaches are the frameworks proposed by Becker et al. (2009), Pöppelbuß and Röglinger (2011), and De Bruin et al. (2005).

Becker et al. (2009) approach maturity model development from a design science perspective, conceptualising maturity models as artefacts intended to solve organisational problems through iterative and rigorously evaluated development processes. Compared to other frameworks, their approach places stronger emphasis on methodological rigor, scientific documentation, and iterative refinement. This makes the framework particularly valuable for ensuring theoretical consistency and research validity. However, despite its structured development logic, the framework remains relatively abstract regarding the operationalisation of maturity assessments and provides limited guidance on how maturity dimensions should be empirically measured, weighted, or adapted to highly sector-specific environments.

In contrast, Pöppelbuß and Röglinger (2011) shift the focus from procedural rigor toward usability and organisational applicability. Their framework distinguishes between descriptive and prescriptive purposes of maturity models, emphasising not only assessment but also actionable recommendations and decision-support mechanisms. Compared to Becker et al. (2009), this approach provides a stronger practical orientation and recognises that maturity models should support organisational transformation rather than merely evaluate current conditions. Nevertheless, the framework is primarily principle-driven and less explicit regarding how models should be operationalised, empirically validated, or maintained within rapidly evolving digital environments.

De Bruin et al. (2005) provide a more operational and process-oriented perspective through a six-phase framework consisting of scope, design, populate, test, deploy, and maintain. Unlike the more conceptual approaches of Becker et al. (2009) and Pöppelbuß and Röglinger (2011), this framework offers clearer procedural guidance for translating maturity model concepts into implementable assessment structures. Its emphasis on deployment and continuous maintenance is particularly important in dynamic technological domains. However, although the framework acknowledges the need for adaptation over time, it was developed prior to the emergence of AI-driven, real-time, and highly autonomous data eco-systems, limiting its ability to fully address the complexity of contemporary big data-intensive sectors such as telecommunications.

Collectively, these frameworks demonstrate a gradual evolution in maturity model development from methodological rigor (Becker et al., 2009), toward usability and prescriptive applicability (Pöppelbuß and Röglinger, 2011), and finally toward operational implementation and continuous adaptation (De Bruin et al., 2005). Despite their contributions, existing frameworks remain largely generic and provide limited guidance for developing sector-specific BDMMs capable of addressing the technological interdependencies, real-time analytical capabilities, and dynamic operational environments characteristic of the telecommunications industry.

3.2 Operationalisation of BDMMs

The operationalisation of BDMMs refers to the transformation of conceptual maturity dimensions into measurable and implementable assessment structures, enabling organisations to assess maturity levels and identify capability gaps systematically (Pörtner et al., 2025). Most maturity models follow a sequential progression logic, where organisations advance through predefined maturity levels representing increasing analytical, technological, and organisational capabilities (Pöppelbuß and Röglinger, 2011). This progression enables organisations not only to assess their current state, but also to identify capability gaps and define strategic pathways for improvement.

Despite this common logic, maturity models differ considerably in how they operationalise assessment structures. One major distinction concerns the evaluative structure of the model. Single-level models generate an overall maturity score, providing a simplified and easily interpretable assessment of organisational capability. While this approach supports benchmarking and ease of use, it may oversimplify complex organisational realities by masking variation across different capability areas. In contrast, multi-level models assess maturity across multiple dimensions such as governance, infrastructure, analytics, strategy, and organisational culture. Compared to single-level approaches, multi-level structures provide greater analytical depth and enable more precise identification of strengths and weaknesses; however, they also increase model complexity and assessment requirements.

Another important aspect of operationalisation concerns the granularity of maturity levels. Most BDMMs adopt five maturity levels, as this structure is generally considered sufficient to capture organisational progression while maintaining usability and interpretability (Mouhib et al., 2020). Nevertheless, existing models vary in the number and definition of maturity levels depending on their intended purpose, domain specificity, and assessment complexity. Although higher granularity may provide more detailed differentiation between maturity stages, excessively complex maturity structures may reduce usability and practical implementation, particularly in rapidly evolving and data-intensive environments.

Overall, the operationalisation of BDMMs reflects an ongoing balance between analytical depth, contextual specificity, usability, and practical applicability. While existing approaches provide useful foundations for organisational assessment, many remain relatively generic and offer limited guidance regarding how maturity structures should accommodate sector-specific operational complexity, dynamic analytical capabilities, and evolving technological ecosystems such as those found in the telecommunications industry.

3.3 Research questions

To guide the development of the BDMM, one central research question and one sub-question have been formulated, as follows:

- Main research question: what constitutes a refined and operationalised BDMM for the telecommunications sector?
- Sub question 1: What dimensions and sub-dimensions define big data maturity in the telecommunications sector based on the refinement of the core framework?
- Sub question 2: What evaluative structure supports the assessment of big data maturity in the telecommunications sector?
- Sub question 3: What levels of granularity and measurement criteria characterise the operationalisation of the model?
- Sub question 4: What are the relative weights of the dimensions and sub-dimensions in the proposed model?

4 Methodology

4.1 Research design

This research adopts a design science research (DSR) approach, grounded in the principles of artefact creation and evaluation (Simon, 1996; Hevner et al., 2004). It employs a mixed-methods strategy that integrates qualitative and quantitative techniques to systematically develop, refine, and validate a BDMM tailored to the telecommunications sector. DSR is defined as research that creates and evaluates purposeful artefacts designed to address identified problems (Venable and Baskerville, 2012). The suitability of DSR for maturity model development has been further emphasised in recent research, as it enables the iterative design, refinement, and evaluation of structured capability assessment artefacts grounded in both theory and practice (Korsten et al., 2025).

A DSR approach was selected because the purpose of this study is not merely to explain big data maturity in telecommunications, but also to develop and validate a practical assessment artefact. Compared with purely explanatory research approaches, DSR emphasises the development of innovative solutions with both theoretical and practical relevance. The use of mixed methods further strengthens the study by combining qualitative expert insights with quantitative validation, allowing the model to be both conceptually grounded and empirically refined.

In line with this paradigm, and as presented in Table 1, the present study aims to design a sector-specific BDMM to support strategic performance in telecommunications organisations. More specifically, the methodological objectives are to identify the key dimensions and sub-dimensions of big data maturity, refine these through expert evaluation, and translate them into a structured, quantifiable, and practically applicable assessment framework.

Table 1 Design science research

DSR component	*Purpose in this study*	*Methods applied*	*Expected outcome*
Problem identification	Identify limitations of generic BDMMs in telecom	Literature review	Research gap definition
Artefact design	Develop telecom-specific maturity framework	Conceptual modelling	Core framework
Refinement and validation	Assess relevance and structure of dimensions	Expert evaluation	Refined maturity model
Operationalisation	Transform framework into measurable assessment tool	Weighting and multi-criteria analysis	Operational maturity assessment mechanism

Following DSR principles (Hevner et al., 2004; Venable and Baskerville, 2012), the study proceeded through iterative phases of problem identification, artefact design, expert-driven refinement, and operational evaluation. The proposed artefact, a sector-specific BDMM for telecommunications, was progressively refined and operationalised through qualitative and quantitative procedures to ensure conceptual validity, contextual relevance, and practical applicability.

4.2 Sample

This section outlines the expert sample involved in the study and the distribution of participants across the different phases of model development. Purposive sampling was used to select 50 participants, as this approach enables the recruitment of individuals with specific expertise relevant to the research objectives (Howitt and Cramer, 2011; Patton, 2015). The inclusion criteria required participants to:

1 represent both industry and academia

2 demonstrate expertise in big data

3 possess a minimum of ten years of professional experience in the telecommunications sector.

To ensure adequate representation, participants were selected based on diversity criteria, including representation from multiple countries such as Kosovo, the Netherlands, Croatia, Bosnia and Herzegovina, Slovenia, Spain, Montenegro, Albania, Austria, Estonia, Sweden, Turkey, Finland, Norway, Germany, and Switzerland, as well as representation from both academia and industry. The expert panel included telecommunications managers, managing directors, heads of radio networks, mobile core architects, heads of engineering, big data specialists, network engineers, data analysts, researchers, and academic experts with extensive experience in telecommunications.

The 50 experts were organised into three respondent groups: group 1 (n = 10), group 2 (n = 20), and group 3 (n = 20), with representation from both academia and industry. Table 2 presents the distribution of respondent groups and their involvement across the model development phases. Participation was phase-specific, with some experts contributing to more than one phase of the study. In phase 1, group 1 contributed to the development of the core framework, resulting in ten expert responses. In phase 2, groups 1 and 2 participated in model refinement and validation, resulting in 30 expert responses. In phase 3, groups 2 and 3 were invited to define the maturity scale, with a final response of 25 experts (5 from group 2 and 20 from group 3). The difference between the total sample (50 experts) and phase-specific response counts is explained by the iterative study design, in which some experts participated in multiple phases while participation in later phases depended on response availability. This phased participation supported iterative validation, increased diversity of perspectives, and strengthened the contextual relevance and practical applicability of the proposed maturity model.

Table 2 Phases of the model development

Model development phase	*Objective*	*Expert groups involved*	*Responses*
Core framework development	Initial conceptualisation of dimensions and sub-dimensions	Group 1	10
Model refinement and validation	Iterative evaluation and refinement of the framework	Group 1 + Group 2	30
Maturity scale operationalisation	Definition of evaluative structure, granularity, and weighting	Group 2 + Group 3	25

Participation was voluntary, and all experts provided informed consent prior to participation. Data were collected and processed confidentially and used exclusively for research purposes.

4.3 Data collection procedure

The data collection process was conducted using a mixed-methods approach integrating both qualitative and quantitative techniques. In the initial phase, qualitative data were collected through semi-structured interviews with experts from the telecommunications industry and academia. This phase aimed to support the development of the core framework by identifying relevant dimensions and sub-dimensions of big data maturity within telecommunications environments.

Subsequently, a Delphi-inspired iterative expert refinement process was employed to support model validation, refinement, and progressive consensus development across successive phases of the study. The process involved three evaluation rounds, during which experts reviewed the proposed framework, provided feedback, and assessed revisions derived from previous rounds. Expert feedback from each round was synthesised and used to refine the framework before redistribution. Consensus was assessed through convergence in quantitative ratings and qualitative agreement regarding the relevance, clarity, and completeness of model components.

In the subsequent phases, quantitative data were collected through structured questionnaires in which experts evaluated the relevance and relative importance of dimensions and sub-dimensions and contributed to defining the evaluative structure, maturity granularity, and weighting mechanisms of the model. The integration of qualitative expert insights and quantitative validation procedures ensured a comprehensive and methodologically robust data collection process.

4.4 Research instruments

For the purposes of this study two self-report questionnaires were developed, as follows:

1. The model refinement questionnaire combined open-ended and structured items designed to evaluate the relevance, clarity, distinctiveness, and completeness of the proposed dimensions and sub-dimensions.
2. The maturity scale questionnaire, which focused on evaluative structure, maturity granularity, weighting of the dimensions and sub-dimensions, and operational applicability of the proposed framework.

Structured items were primarily rated using a five-point Likert scale ranging from 1 (low relevance) to 5 (high relevance), while open-ended items enabled experts to provide qualitative suggestions for refinement.

4.5 Data analysis

A mixed-methods analytical approach was employed to support both the refinement and operationalisation of the proposed model. Quantitative data were analysed using Stata, while qualitative data were processed using ATLAS.ti. Descriptive statistical analysis was conducted on expert ratings to summarise central tendencies and variability across model dimensions and sub-dimensions. Specifically, mean scores were used to assess relevance and weighting, while standard deviation (SD) and coefficient of variation (CV) were calculated to evaluate the level of consensus among experts.

In parallel, qualitative data derived from expert feedback were analysed through systematic coding procedures in ATLAS.ti. Codes were generated inductively from the data, and their frequency and distribution were examined to identify recurring patterns. The interpretation of these codes enabled the identification of key themes, which informed decisions regarding the modification, refinement, and consolidation of model elements.

To support the operationalisation of the model, a hierarchical weighting approach, conceptually aligned with the analytic hierarchy process, was applied. Experts allocated relative importance scores across dimensions and sub-dimensions, which were subsequently used to calculate global and local weights. These coefficients form the basis of the model's scoring system, providing a structured representation of organisational maturity across dimensions.

The integration of qualitative thematic interpretation and quantitative expert evaluation enabled methodological triangulation and strengthened the validity of refinement and operationalisation decisions.

5 Findings

This section presents the empirical findings from the refinement and operationalisation of the proposed BDMM. The findings are organised into two parts. First, the refinement process is presented through quantitative relevance assessment, qualitative expert feedback, and integrated model restructuring. Second, the operationalisation process is presented through the evaluative structure, maturity granularity, and weighting coefficients of dimensions and sub-dimensions.

5.1 Refinement of the model

This subsection presents how expert feedback informed the refinement of the initial core framework into the final sector-specific maturity model.

5.1.1 Quantitative assessment of dimensions' relevance

This subsection presents the findings indicating how relevant the main dimensions in the BDMM are. At this point, the focus is on the experts' evaluation of the relevance of each main dimension, not the sub-dimensions.

Table 3 Relevance of the dimensions

Dimensions	*Highly relevant*	*Mean*	*Std. deviation*
Data governance	100%	5	0
Market strategy	76%	4.76	0.43
Network performance	88%	4.88	0.33
Business development	96%	4.96	0.2
Customers	76%	4.68	0.61
Data analytics capabilities	88%	4.72	0.97
Investments	92%	4.88	0.43
Network modernisation	72%	4.68	0.55
Organisation	24%	3.64	1.05

Items in the model refinement questionnaire were rated using a five-point Likert scale ranging from 1 (not relevant) to 5 (highly relevant). for reporting purposes, the 'highly relevant (%)' indicator presented in the findings reflects the percentage of experts assigning the highest score (5) to each dimension or sub-dimension. The remaining percentage corresponds to responses distributed across lower rating categories (1–4).

As presented in the Table 3, the findings indicate a generally high level of expert agreement regarding the relevance of most dimensions included in the proposed BDMM. Dimensions such as data governance, business development, network performance, and investments demonstrate particularly strong consensus, reflected by very high mean values and low SDs. Data governance achieved perfect agreement among experts (mean = 5.00; SD = 0.00), highlighting its perceived centrality in assessing big data maturity within telecommunications organisations. Similarly, business development (mean = 4.96; sd = 0.20) and network performance (mean = 4.88; SD = 0.33) were consistently evaluated as highly relevant, suggesting that experts view strategic business capabilities and operational network efficiency as critical components of data-driven maturity in the telecommunications sector.

In contrast, the organisation dimension received the lowest mean score (mean = 3.64) and the highest SD (SD = 1.05), indicating substantial divergence in expert perceptions regarding its distinctiveness and relevance within the model. This variability suggests conceptual ambiguity and potential overlap between organisational capabilities and other dimensions such as business development, investments, or data governance. A similar, though less pronounced, pattern was observed for data analytics capabilities, which demonstrated relatively high variability (SD = 0.97) despite a high mean score. This may reflect differing expert interpretations regarding whether analytics capabilities should be treated as an independent organisational dimension or as an embedded capability distributed across multiple operational and strategic areas.

Overall, the findings reveal a clear distinction between dimensions perceived as foundational and well-established within telecommunications environments, such as governance, network performance, and business-oriented capabilities, and dimensions viewed as more conceptually diffuse or overlapping. These patterns provided important empirical guidance for the subsequent refinement process, particularly regarding the consolidation, restructuring, or removal of dimensions with lower conceptual clarity and weaker expert consensus.

Table 4 Quantitative relevance assessment of sub-dimensions

Dimension	*Highest rated sub-dimensions*	*Mean*	*Lowest rated sub-dimensions*	*Mean*
Data governance	Data reliability	5.00	Data infrastructure/data storage	3.44
Market strategy	Products/services	4.92	Sales	3.68
Network performance	Network planning and optimisation	5.00	Field maintenance	3.44
Business development	Business intelligence	5.00	Prediction	4.36
Customers	Customer migration	4.80	Customer demographics	4.12
Data analytics capabilities	Data software analytics	4.60	Human resource analytics capabilities	4.56
Investments	Human resource investments	4.84	Data infrastructure investments	4.80
Network modernisation	Innovation	4.96	—	—

As presented in the Table 4, the results indicate that most sub-dimensions achieved high mean values (above 4.0), confirming their strong perceived relevance in assessing big data maturity in telecommunications. Sub-dimensions such as data reliability, business intelligence, and network planning and optimisation demonstrate perfect consensus (mean = 5.00; SD = 0.00), highlighting their critical importance. In contrast, sub-dimensions such as sales, field maintenance, and network monitoring show higher SD values (>1.0), indicating greater variability in expert opinions and suggesting areas of conceptual divergence. Additionally, elements like data infrastructure and data storage exhibit lower mean values, implying comparatively lower perceived relevance or maturity within the proposed framework.

Beyond confirming overall relevance, the sub-dimension analysis reveals relative prioritisation patterns rather than clear distinctions between relevant and irrelevant components. Although all sub-dimensions were considered important, experts assigned higher importance to those more directly associated with strategic and operational core functions within telecommunications.

5.1.2 Qualitative insights for model refinement

This section presents the qualitative findings derived from expert feedback collected during the refinement process. The analysis, presented in Table 5, focused on identifying recurring conceptual themes related to the clarity, structure, relevance, and practical applicability of the proposed BDMM.

Table 5 Thematic interpretation table

Theme	*Representative expert concern*	*Refinement implication*
Addition of new elements	Need to integrate emerging capabilities such as AI, competitive intelligence, and customer experience	Integration of AI, technology scouting, competitive intelligence, and customer-related sub-dimensions
Conceptual overlap	Overlap between dimensions, particularly organisation and data analytics capabilities	Consolidation and removal of overlapping elements
Terminology standardisation	Inconsistent or ambiguous terminology across dimensions and sub-dimensions	Standardisation and refinement of terminology
Structural simplification	Excessive fragmentation of operational components	Merging of operationally related sub-dimensions
Strategic orientation enhancement	Need for stronger alignment with strategic and future-oriented telecom capabilities	Expansion of strategic and innovation-oriented capabilities
Practical applicability	Technical complexity reduced usability for organisational assessment	Improved interpretability and applicability of the framework

The qualitative findings revealed several important refinement patterns. Experts emphasised the need to strengthen the strategic and future-oriented orientation of the model through the inclusion of capabilities related to artificial intelligence, competitive intelligence, and customer experience. At the same time, several dimensions and sub-dimensions were perceived as conceptually overlapping, particularly organisation and data analytics capabilities, leading to consolidation and structural simplification. Experts also highlighted the importance of terminology standardisation and clearer categorisation of operational activities to improve interpretability and practical applicability. Overall, the qualitative feedback played a critical role in enhancing the conceptual clarity, sector relevance, and operational usability of the refined BDMM.

5.1.3 Integrated refinement of the model

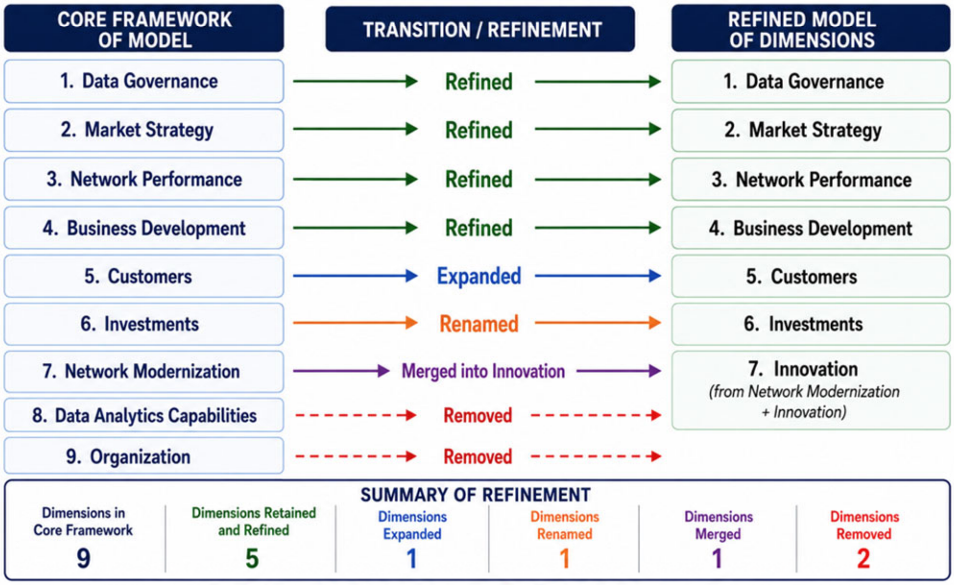
The refinement of the maturity model from its core framework to the final version was shaped by expert feedback, which provided insights into relevance, linguistic aspect, and structural clarity. Based on these contributions, some elements were removed, some terms were standardised, and new sub-dimensions were added.

Figure 1 illustrates the transition from the initial core framework to the refinement of the BDMM dimensions. Six dimensions, including: ‘data governance’, ‘market strategy’, ‘network performance’, ‘business development’, ‘customers’ and ‘investments’, remained the same. Network modernisation was consolidated into a broader innovation dimension. conversely, the organisation and data analytics capabilities dimensions were removed during the refinement process, as experts indicated conceptual overlap with other dimensions or insufficient distinctiveness.

A similar refinement approach was applied at the sub-dimension level, where elements were evaluated based on expert feedback, leading to the retention of highly relevant components, the consolidation of overlapping elements, and the refinement or removal of those lacking distinctiveness. At the sub-dimension level, data governance was refined by removing overlapping elements such as data infrastructure and data storage, while standardising terminology through changes such as data protection to data security and fraud detection to fraud management. Market strategy was restructured by consolidating overlapping elements into broader constructs, resulting in the introduction of campaign strategy and the addition of competitive intelligence as a new sub-dimension. Network performance was simplified by merging operational components into network operations and renaming network support to quality assurance to better reflect its functional role. The business development dimension required only minor adjustments, primarily involving the renaming of prediction to forecasting, indicating strong initial conceptual alignment. In contrast, the customers dimension underwent more substantial refinement through terminology standardisation and conceptual clarification, resulting in sub-dimensions such as customer segmentation, user analytics, churn management, internal migration tracking, and customer experience. This reflects the evolving and context-dependent nature of customer analytics in telecommunications. The Investments dimension remained structurally unchanged, with minor terminology refinements emphasising data platform investments and skills investments, reinforcing the dual importance of technological and human capital. The innovation dimension was redefined to reflect a lifecycle perspective, integrating artificial intelligence, technology scouting, and network modernisation as interconnected components of continuous technological advancement.

Figure 1 illustrates the transition from the initial core framework to the refined BDMM following expert evaluation and iterative refinement through the DSR process. The initial framework consisted of nine dimensions derived from the literature: Data governance, market strategy, network performance, business development, customers, investments, network modernisation, data analytics capabilities, and organisation. Following expert consultation and Delphi-based refinement, the model was streamlined into seven dimensions. Five dimensions (data governance, market strategy, network performance, business development, and customers) were retained but refined to improve conceptual clarity and sector relevance. The customers dimension was further expanded to better capture customer-centric analytical capabilities in telecommunications. The Investments dimension was retained with minor terminological refinement to better reflect investment in data platforms and skills. A major structural change involved the transformation of network modernisation into the broader innovation dimension, which incorporated both network modernisation and emerging technology adoption, including AI and technology scouting. Two dimensions, data analytics capabilities and organisation, were removed because experts considered their constructs to overlap substantially with other dimensions rather than representing standalone maturity domains. Overall, the refinement process reduced the framework from nine to seven dimensions, improving conceptual coherence, reducing redundancy, and producing a more sector-specific and practically applicable maturity model for telecommunications.

Figure 1 Transitioning from core framework to model refinement of dimensions (see online version for colours)



The final framework consists of seven dimensions that collectively capture both the technical and strategic dimensions of big data maturity in telecommunications. Unlike generic maturity models, which often emphasise technological readiness or analytical capabilities in isolation, the proposed framework reflects the sector-specific interdependence between data governance, network operations, customer intelligence, strategic market responsiveness, investment readiness, and innovation capacity. The selection and refinement of these dimensions were guided by literature synthesis and iterative expert consensus to ensure both theoretical coherence and practical applicability.

5.2 *Operationalisation of the model*

This subsection presents the operationalisation of the refined model, including the evaluative structure, maturity granularity, and weighting coefficients used to translate the framework into an assessment mechanism.

5.2.1 *Definition of the evaluative structure*

This section presents the results provided by the experts regarding their preferred evaluative structural approach for the BDMM. The findings reflect how experts believe the model should be organised in order to most accurately capture variations in maturity across dimensions and sub-dimensions. Experts were asked to indicate whether the model should follow a single-level structure, a multi-level structure, or a combined approach that integrates both. The findings demonstrate a strong expert preference for the combined approach (84%), indicating that telecommunications big data maturity assessment requires both an overall maturity score and dimension-level evaluation. A smaller proportion of experts preferred the Multi-model approach (16%), while no respondents supported a single-model structure, suggesting that a solely aggregated maturity score is insufficient for capturing the complexity of telecommunications environments. Overall, the results highlight a clear consensus in favour of a more comprehensive and balanced evaluative structure. This preference reflects the multidimensional nature of big data maturity in telecommunications, where both overall benchmarking and dimension-level diagnosis are necessary to support meaningful assessment and strategic decision-making.

5.2.2 Development of the granularity

This section presents the results regarding expert perspectives on the appropriate level of granularity for the maturity scale. The five-stage maturity scale was initially proposed by the author, informed by insights from the literature review as well as the specific purpose of this model: assessing big data maturity in the telecommunications sector within a strategic planning context. Experts were asked to evaluate whether the existing five-stage maturity structure was sufficiently detailed to capture meaningful distinctions in organisational capability, or whether modifications were necessary. The five stages proposed by the author are presented in Table 6.

Table 6 Granularity-stages proposed by the author

Stage	*Score range (0–100)*	*Meaning*
Stage 1 – Pre-data/ad hoc	0–20	Data use is fragmented, manual, and reactive
Stage 2 – Operational efficiency	21–40	Data supports reporting and operational monitoring
Stage 3 – Diagnostic analytics	41–60	Data is integrated and used to explain past performance
Stage 4 – Strategic planning	61–80	Analytics informs planning, optimisation, and strategy
Stage 5 – Autonomous and adaptive	81–100	Advanced analytics and automation drive decisions

The findings indicate strong expert agreement regarding the suitability of the proposed five-level maturity structure, with 88% of respondents considering the model sufficiently granular for assessing big data maturity in telecommunications. This suggests that the proposed progression adequately balances analytical depth and practical usability.

The five-stage structure also reflects a logical maturity trajectory, progressing from fragmented and reactive data usage toward autonomous, adaptive, and analytics-driven decision systems, thereby aligning with capability maturity principles while preserving interpretability for practical assessment.

5.2.3 Determination of the dimensions and sub-dimensions weights

This section presents the weighting coefficients derived from expert evaluations, reflecting the relative importance assigned to each dimension and sub-dimension within the proposed BDMM. The global weights of the dimensions were calculated based on the mean scores assigned by 25 experts, each of whom distributed 100 points across the seven dimensions according to their perceived significance in assessing big data maturity in telecommunications organisations.

Subsequently, experts distributed an additional 100 points among the sub-dimensions within each parent dimension. The mean score assigned to each sub-dimension represented its relative importance within that dimension. To operationalise the weighting structure, the local weight of each sub-dimension was calculated by multiplying the global weight of the parent dimension (GWd) by the relative importance proportion assigned to the sub-dimension (LWsd) as follows:

$$\text{LWfinal} = \text{GWd} \times \text{LWsd}$$

where

- LWfinal represents the final local weight of the sub-dimension
- GWd represents the global weight of the parent dimension
- LWsd represents the relative importance proportion assigned to the sub-dimension based on expert evaluation.

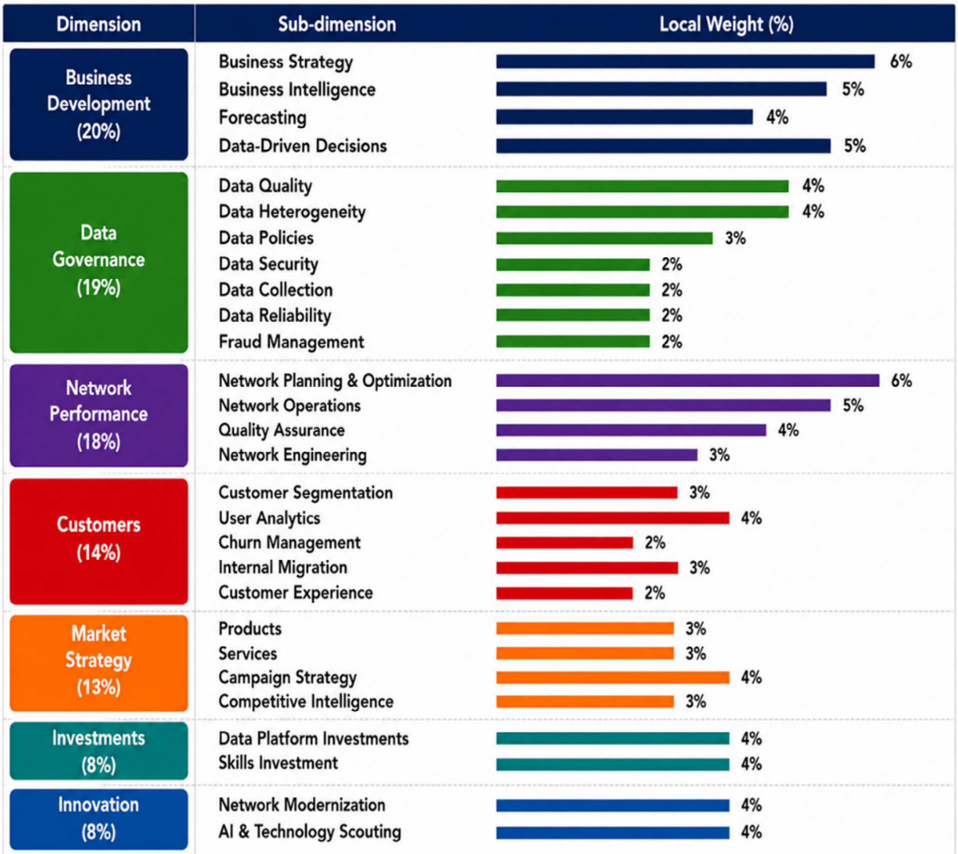
This hierarchical weighting approach was selected because it captures the nested structure of the model, where sub-dimensions contribute proportionally to their parent dimensions, and dimensions contribute according to their strategic importance in the overall maturity score.

Figure 2 presents the resulting global and local weighting coefficients, together with agreement indicators reflecting the relative importance assigned by experts to each dimension and sub-dimension of the proposed model.

The weighting analysis revealed clear strategic prioritisation patterns across the proposed big data maturity dimensions. Business development emerged as the most influential dimension (20%), followed closely by data governance (19%) and network performance (18%). This distribution suggests that experts perceive big data maturity in telecommunications not merely as a technological capability, but as a strategic and operational enabler closely linked to organisational decision-making, network efficiency, and business transformation. In contrast, dimensions such as investments and innovation received comparatively lower global weights (8% each), although experts demonstrated strong internal consistency regarding their importance. This suggests that while innovation and investments are recognised as necessary enabling conditions, experts perceive governance, business-oriented capabilities, and network performance as more immediate determinants of organisational maturity.

To assess the level of agreement among experts, both SD and CV were calculated for all sub-dimensions. The results demonstrate an overall satisfactory level of consensus across the expert panel. The analysis of weighting coefficients revealed generally strong expert consensus regarding the relative importance of most dimensions and sub-dimensions within the proposed big data maturity model. Particularly strong agreement was observed for business development, data governance, investments, innovation, and network performance, indicating a shared perception of these areas as central components of big data maturity in telecommunications. In contrast, the customers dimension exhibited the highest variability, suggesting that experts differ more substantially in how they prioritise customer-related analytical capabilities. For completeness, the detailed weighting coefficients together with the corresponding SD and CV values used to assess expert agreement are reported in Appendix B.

Figure 2 Global and local weighting coefficients of the proposed BDMM (see online version for colours)



The weighting results revealed an important shift in how big data maturity is conceptualised in telecommunications. Rather than prioritising infrastructure or technological sophistication alone, experts assigned greater importance to business-oriented and governance-related dimensions. This suggests that maturity is increasingly understood as the organisational ability to transform data into strategic value, rather than merely possessing advanced analytical tools or technological infrastructure.

6 Discussion

The findings demonstrate that big data maturity in telecommunications represents a multidimensional organisational capability emerging through the interaction of governance structures, strategic alignment, operational performance, customer analytics, and innovation-oriented capabilities. Rather than reflecting solely technological readiness, the proposed model indicates that big data maturity within telecommunications environments is shaped by the organisation's ability to integrate data-driven capabilities across strategic, operational, and decision-making processes. This reflects the increasingly complex and data-intensive nature of modern telecommunications ecosystems, where competitive advantage depends not only on technological infrastructure, but also on the effective orchestration of analytical, organisational, and innovation-related capabilities.

From a theoretical perspective, the findings extend the principles of RBT by demonstrating that big data maturity in telecommunications is not determined exclusively by technological assets, but also by the organisation's capacity to integrate governance mechanisms, business-oriented capabilities, and innovation processes into coherent operational systems. The strong expert consensus observed in dimensions such as data governance, business development, and network performance suggests that telecommunications organisations perceive data quality, strategic alignment, and operational optimisation as foundational organisational resources. These findings reinforce prior arguments that sustainable competitive advantage increasingly derives from the effective integration of data, analytics, infrastructure, and human capabilities (Barney, 1991). In particular, the strong agreement regarding investments and innovation highlights the dual importance of technological infrastructure and human capital, suggesting that organisational value is generated not merely through data availability, but through the dynamic capabilities required to transform data into strategic and operational outcomes.

At the same time, the findings reveal important variations across dimensions, indicating that big data maturity does not evolve uniformly across organisational capabilities. The relatively low variability observed in data governance and network performance suggests that these domains are highly standardised and operationally embedded within telecommunications environments. This is consistent with the infrastructure-intensive and highly regulated nature of the telecommunications sector, where reliability, security, interoperability, and performance management are essential operational requirements. In contrast, the customers dimension demonstrated substantially higher variability, indicating that customer-oriented analytical capabilities remain more context-dependent and strategically differentiated across organisations. This distinction reflects the dual nature of telecommunications ecosystems, where infrastructure-related capabilities are shaped by standardisation and operational regulation, whereas customer analytics capabilities are more strongly influenced by organisational strategy, market positioning, customer segmentation practices, and competitive dynamics.

The findings also contribute to the broader literature on big data maturity assessment by addressing several limitations identified in previous studies. Existing maturity models have frequently been criticised for being overly generic, conceptually fragmented, or insufficiently operationalised for sector-specific implementation (Al-Sai et al., 2022; Mouhib et al., 2020). In response to these limitations, the present study proposes a sector-specific and operationalised maturity framework tailored to the telecommunications industry. Unlike prior models that primarily emphasise capability dimensions or conceptual structures, the proposed model integrates dimensions, sub-dimensions, maturity levels, evaluative structures, and weighting mechanisms into a unified assessment framework. Furthermore, whereas previous studies such as Keshavarz et al. (2021) focus primarily on capability identification, the present study advances the literature by operationalising maturity progression through a structured maturity scale and weighted evaluative mechanism capable of supporting organisational benchmarking and strategic capability development.

An additional contribution of this study lies in its methodological approach. The integration of DSR, Delphi-based expert refinement, and quantitative weighting mechanisms provides a systematic and context-sensitive foundation for maturity model development. The iterative refinement process strengthened both the conceptual validity and practical applicability of the proposed framework, while the integration of qualitative and quantitative expert feedback enhanced its sector relevance. Moreover, the strong preference for a combined evaluative structure demonstrates that big data maturity in telecommunications cannot be adequately captured through a single aggregated maturity score alone. Instead, organisations require both a holistic maturity overview and dimension-level insights capable of identifying capability-specific strengths and weaknesses. This dual evaluative logic is particularly important in telecommunications environments characterised by technological interdependencies, dynamic analytical ecosystems, and rapidly evolving digital infrastructures.

From a practical perspective, the proposed model offers telecommunications organisations a structured decision-support framework for assessing big data maturity, identifying capability gaps, and prioritising strategic investments. The weighting structure further enhances practical applicability by distinguishing foundational capabilities, such as data governance, business development, and network performance, from more context-sensitive domains such as customer analytics. This enables organisations to allocate resources more strategically while recognising that maturity development may require differentiated approaches across capability areas. In particular, the relatively high variability observed in customer-related dimensions suggests that organisations may need to adopt more adaptive and context-specific strategies when developing customer analytics and experience-oriented capabilities.

Overall, the findings suggest that big data maturity in telecommunications should be understood as a dynamic and adaptive organisational construct rather than a purely linear technological progression. While certain dimensions, such as governance and operational performance, exhibit relatively stable and standardised characteristics, others remain strongly influenced by organisational strategy, market conditions, and evolving analytical practices. This balance between standardised infrastructure capabilities and context-dependent strategic analytics capabilities enhances the explanatory power of the proposed model and supports its applicability across diverse telecommunications contexts.

7 Conclusions

This study developed and operationalised a sector-specific big data maturity model for the telecommunications industry. The resulting framework consists of seven core dimensions, data governance, market strategy, network performance, business development, customers, investments, and innovation, supported by clearly defined sub-dimensions that collectively capture the strategic, operational, and analytical capabilities shaping big data maturity within telecommunications organisations.

The proposed model integrates both conceptual and operational components through a combined evaluative structure that enables organisations to assess overall maturity while simultaneously evaluating capability-specific performance across dimensions. In addition, the model incorporates a five-level maturity progression framework supported by structured measurement criteria and expert-based weighting mechanisms, allowing organisations to identify capability gaps, prioritise strategic investments, and support data-driven transformation initiatives.

By integrating weighted dimensions, maturity granularity, and sector-specific operational requirements, the study contributes to existing big data maturity literature by moving beyond generic assessment approaches toward a more context-sensitive and practically applicable framework tailored to telecommunications environments. More broadly, the findings highlight the importance of developing sector-specific maturity models capable of capturing the operational complexity, technological interdependencies, and evolving analytical ecosystems characterising contemporary digital industries.

The unique contribution of this study lies in the development of a sector-specific and operationalised maturity model that combines conceptual refinement, expert-driven validation, weighted scoring mechanisms, and maturity stage granularity within a single assessment framework. Unlike generic BDMMs, the proposed framework explicitly reflects the operational and strategic realities of telecommunications environments.

From a theoretical perspective, the study extends RBT and dynamic capabilities perspectives by demonstrating that big data maturity depends not only on technological resources, but also on the organisational capability to integrate governance, analytics, strategic decision-making, and innovation into sustained value creation.

From a managerial perspective, the proposed model offers telecommunications managers a practical diagnostic tool for benchmarking organisational maturity, identifying capability gaps, prioritising resource allocation, and supporting strategic digital transformation initiatives. While the limitations and future research directions are discussed in Section 8, further large-scale empirical validation is needed to strengthen the model's generalisability and predictive applicability across diverse telecommunications contexts.

8 Limitations and future research

Development and operationalisation of the proposed model relied primarily on expert-based evaluation, which may introduce subjective perspectives despite the inclusion of both academic and industry participants. Second, although the expert sample was purposefully selected to ensure domain relevance and diversity, the relatively limited sample size may restrict the broader generalisability of the findings across different telecommunications contexts and markets.

In addition, the study focused on the conceptual refinement and operationalisation of the maturity model rather than its large-scale empirical implementation within telecommunications organisations. As a result, the practical performance and predictive validity of the model in real organisational environments remain to be further examined. Furthermore, the rapidly evolving nature of big data, artificial intelligence, and telecommunications technologies suggests that maturity dimensions and weighting structures may require continuous adaptation over time.

Future research should focus on large-scale empirical validation of the model across different telecommunications markets and organisational contexts. Longitudinal studies could further examine how big data maturity evolves over time and how maturity progression influences organisational performance and digital transformation outcomes.

Future studies may also explore the integration of additional technological capabilities, including AI-driven automation, real-time analytics, and emerging network technologies, to ensure the continued relevance and adaptability of the proposed maturity framework.

Declarations

ChatGPT, developed by OpenAI, was used solely for language editing, grammar improvement, and text refinement purposes. The authors take full responsibility for the originality, accuracy, and scientific content of the manuscript.

Informed consent was obtained from all participants involved in the study prior to data collection. All procedures performed in this study involving human participants were conducted in accordance with institutional and ethical research standards. Participation was voluntary, and all responses were treated confidentially.

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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Appendix A

Table A1 Summary of dimensions and sub-dimensions of the proposed big data maturity model

Dimension	*Weight*	*Short definition*
Business development	20%	Use of big data for strategic growth and business decision-making
Business strategy	6 %	Data supports long-term strategic planning.
Business intelligence	5%	Data is converted into actionable insights.
Forecasting	4%	Analytics predicts trends, demand, and risks.
Data-driven decisions	5%	Decisions are based on analytical evidence.
Data governance	19%	Management and control of data assets across the organisation
Data quality	4%	Data is accurate, complete, and timely.
Data heterogeneity	4%	Diverse data sources are integrated effectively.
Data policies	3%	Formal rules govern data access and usage.
Data security	2%	Data is protected from breaches and misuse.
Data collection	2%	Data acquisition is systematic and scalable.
Data reliability	2%	Data remains consistent and trustworthy.
Fraud management	2%	Analytics supports fraud detection and prevention.
Network performance	18%	Optimisation of telecom network operations using analytics
Network planning and optimisation	6%	Analytics improves capacity and resource planning.
Network operations	5%	Network performance is monitored in real-time.
Quality assurance	4%	Service quality and reliability are ensured.
Network engineering	3%	Analytics supports network design and maintenance.
Customers	14%	Use of analytics to understand and improve customer behaviour
Customer segmentation	3%	Customers are grouped by behaviour and needs.
User analytics	4%	Customer usage patterns are continuously analysed.
Churn management	2%	Analytics predicts and reduces churn.
Internal migration	3%	Customer movement across services is analysed.
Customer experience	2%	Data improves satisfaction and service quality.
Market strategy	13%	Use of analytics for market positioning and competitiveness
Products	3%	Data supports product decisions and development.
Services	3%	Analytics optimises service offerings.
Campaign strategy	4%	Marketing campaigns are data-driven.
Competitive intelligence	3%	Market and competitor trends are monitored.
Investments	8%	Allocation of resources for big data capability development
Data platform investments	4%	Investment in data infrastructure and platforms.
Skills investment	4%	Investment in analytics talent and skills.
Innovation	8%	Use of emerging technologies for transformation and growth

Table A1 Summary of dimensions and sub-dimensions of the proposed big data maturity model (continued)

Dimension	*Weight*	*Short definition*
Network modernisation	4%	Network infrastructure is modernised using advanced digital technologies.
Ai & scouting	4%	AI opportunities and new technologies are explored.

Appendix B

Table A2 Coefficients of dimensions and sub-dimension significance

Dimension	*Global weight (%)*	*Sub-dimension*	*Local weight (%)*	*SD*	*CV*
Business development	20	Business strategy	6	2.99	0.10
		Business intelligence	5	4.75	0.20
		Forecasting	4	2.38	0.11
		Data-driven decisions	5	4.25	0.16
Data governance	19	Data quality	4	3.76	0.20
		Data heterogeneity	4	3.88	0.21
		Data policies	3	2.34	0.17
		Data security	2	2.24	0.17
		Data collection	2	2.03	0.17
		Data reliability	2	2.28	0.19
		Fraud management	2	2.21	0.20
Network performance	18	Network planning and optimisation	6	5.44	0.16
		Network operations	5	3.67	0.14
		Quality assurance	4	4.52	0.21
		Network engineering	3	5.89	0.33
Customers	14	Customer segmentation	3	6.04	0.27
		User analytics	4	8.35	0.31
		Churn management	2	6.54	0.40
		Internal migration	3	6.44	0.33
		Customer experience	2	5.66	0.39
Market strategy	13	Products	3	0.00	0.00
		Services	3	0.00	0.00
		Campaign strategy	4	5.15	0.18
		Competitive intelligence	3	5.40	0.25
Investments	8	Data platform investments	4	4.00	0.08
		Skills investment	4	4.00	0.08
Innovation	8	Network modernisation	4	5.26	0.11
		AI and scouting	4	5.26	0.10