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Assessment of process capabilities in transition to a data-driven organisation: A multidisciplinary approach

Mert O. Gökalp | Kerem Kayabay | Ebru Gökalp | Altan Koçyiğit | P. Erhan Eren

Informatics Institute, Middle East Technical University, Ankara, Turkey

Correspondence
Mert O. Gökalp, Informatics Institute, Middle East Technical University, Ankara 06800, Turkey.
Email: gmert@metu.edu.tr

Abstract

The ability to leverage data science can generate valuable insights and actions in organisations by enhancing data-driven decision-making to find optimal solutions based on complex business parameters and data. However, only a small percentage of the organisations can successfully obtain a business value from their investments due to a lack of organisational management, alignment, and culture. Becoming a data-driven organisation requires an organisational change that should be managed and fostered from a holistic multidisciplinary perspective. Accordingly, this study seeks to address these problems by developing the Data Drivenness Process Capability Determination Model (DDPCDM) based on the ISO/IEC 330xx family of standards. The proposed model enables organisations to determine their current management capabilities, derivation of a gap analysis, and the creation of a comprehensive roadmap for improvement in a structured and standardised way. DDPCDM comprises two main dimensions: process and capability. The process dimension consists of five organisational management processes: change management, skill and talent management, strategic alignment, organisational learning, and sponsorship and portfolio management. The capability dimension embraces six levels, from incomplete to innovating. The applicability and usability of DDPCDM are also evaluated by conducting a multiple-case study in two organisations. The results reveal that the proposed model is able to evaluate the strengths and weaknesses of an organisation in adopting, managing, and fostering the transition to a data-driven organisation and providing a roadmap for continuously improving the data-drivenness of organisations.

1 | INTRODUCTION

Data-driven organisations exploit insights derived from data in basing all business decisions rather than intuitions of managers [1]. McKinsey states that organisations that adopt data-driven decision-making are 19 times more profitable than their non-adopter competitors [2]. Another survey [3] forecasts that data-driven organisations 140% more likely to grant a sustainable competitive advantage in a highly competitive business environment and 78% more likely to grow revenue. Some studies also revealed a direct relationship between the capability of leveraging data-driven decision-making and firm performance [4]. Thus, an increasing number of organisations endeavour to infuse data into their decision-making process. However, this reveals significant organisational concerns as it is embedded in organisational processes and strategy [5]. Organisations mainly face difficulties in generating business value from their data science investments due to a lack of organisational management, alignment, and culture rather than ineffective utilization of data or technologies [6]. In the literature, only a handful of studies are grounded on investigating organisational management capabilities in increasing adoption and integration of data science across the organisation to foster a successful shift to a data-driven organisation.

Data-driven organisations leverage data science to make each business decision based on tangible evidence extracted from data. Data science enables organisations to spur the development of their data-driven decision-making capabilities across the organisation. It is a multidisciplinary domain that requires significant expertise within the mathematics, computer science, statistics, and especially software engineering domains to extract valuable insights from data and improve the businesses' decision-making capabilities [1]. Accordingly, it needs a collaborative work of employees from different backgrounds, disciplines, and business units. This necessitates having sustainable organisational capabilities to manage and orchestrate data science endeavours throughout the organisation. On the one hand, data and technology capabilities are significant facilitators of data-driven organisations in transforming data into business insights and actions. On the other hand, organisational capabilities, including a cultural shift towards data-driven culture, building the right multidisciplinary team, aligning the organisation in a strategic business direction, are the most challenging drivers on the journey in successfully adopting data science and becoming a data-driven organisation [6]. Even though most of the organisations leverage data science methodologies and big data technologies to extract insights from data, the majority of these organisations still make their business decisions based on the experience or intuition of their managers rather than knowledge extracted from data due to organisational concerns, including lack of a data-driven culture [1]. To this end, there is a need to systemically and extensively investigate, define, and manage organisational processes, practices, and capabilities to assist organisations in their transformation initiatives from intuition-driven to a data-driven organisation.

Process capability maturity models (MMs) and standards, such as Capability Maturity Model Integration (CMMI) and Software Process Improvement and Capability dEtermination (SPICE) [12], which is also known as a set of standards, ISO/IEC 330xx, are utilised to evaluate and understand how to implement the value of relatively new technologies and capabilities in an organisational context [7]. They describe fundamental patterns in the assessment of process capabilities and provide directions for improvement. They can be used descriptively to assess the current process capability level. In addition, they also have prescriptive objectives to provide the steps that organisations should undertake to improve their current process capabilities. As a result of the observed benefits of CMMI and ISO/IEC 330xx in the software development domain, they have been customised to different domains, including automotive [8], industry 4.0 [9], and government [10]. Moreover, the applicability of an ISO/IEC 330xx based process capability MM in the data analytics domain is validated in our previous research [11]. Thus, this is a suitable approach to guide organisations in grasping the potential benefits of data science and data-drivenness.

This study aims to develop a process capability MM to evaluate organisational management processes for a successful transition to a data-driven organisation by providing guidance in determining the current organisational processes capability level; presenting opportunities for improvement to move to the next capability level; benchmarking itself against other organisations evaluated with the same model. The proposed Data Drivenness Process Capability Determination Model (DDPCDM) has six capability levels from Level 0: Incomplete to Level 5: Innovating, and it investigates the organisational data-drivenness from a holistic multidisciplinary perspective. We defined critical processes, practices, and capabilities to become a data-driven organisation based on a well-known ISO/IEC 330xx standard family, superseding SPICE [12]. We also evaluated the applicability and usability of the DDPCDM with a multiple-case study approach. The results indicate that the DDPCDM is able to evaluate the strengths and weaknesses of an organisation in transition to a data-driven organisation and providing a roadmap for continuously improving and aligning its organisational management capabilities.

The rest of the paper is organised as follows. Section 2 gives background information and reviews existing literature. We detailed the proposed model, DDPCDM, in Section 3. The data collection, validation, and analysis approaches for the multiple-case study are given in Section 4, and then discuss the results and findings of the case study in Section 5. Finally, we conclude the paper and give future research directions in Section 6.

2 | BACKGROUND AND RELATED WORKS

This section first gives background information about data science, data-driven organisation, and process capability MMs and standards. Then, we discuss the related studies in the scope of this research by systematically reviewing the literature.

2.1 | Data science and data-driven organisation

Data science is a multidisciplinary domain that requires significant expertise within the mathematics, computer science, statistics, and especially software engineering domains to extract valuable insights from data and improve the decision-making capabilities of businesses [1]. As the volume and variety of collected data increases, data science gains more importance for businesses seeking to attain a competitive edge, increase profitability, customer satisfaction and reduce costs by extracting valuable and actionable insights from data [13, 14]. It enables organisations to spur the development of their data-driven decision-making capabilities across the organisation. Data-driven organisations make each strategic decision based on the interpretation of data and analytics by utilising the data science approaches. Thus, organisations are increasingly utilising data science principles, algorithms, and methodologies to develop software products in analysing data. Data scientists and data engineers are becoming a critical part of software development teams as software developers, architects, designers, and testers [15]. Most organisations primarily invest in data and technology capabilities to integrate data science into their daily operations. However, these businesses experience difficulties in managing organisation management processes to transition to become a data-driven organisation successfully. Thus, there is a need to develop a standardised framework by assessing and generating a roadmap for improving these processes in a standardised manner to support organisations in obtaining sustainable benefits from their data science investments and cope with rapidly changing and challenging business environments. This framework should also enable organisations to integrate data science across the organisation and external customers, suppliers, and business units to envision opportunities for accelerating the transition to a data-driven organisation [1].

2.2 | Process capability and MMs and standards

Process capability MMs and related standards provide a common framework to support organisations in evaluating their process capabilities and organisational maturity levels and also revealing gaps or weaknesses that organisations should iteratively improve [16]. They also provide a common vision and language for both practitioners and scholars and an evolutionary path to prioritising actions for long-term productivity and product quality. Moreover, they define a set of criteria, objectives, and characteristics to reach a particular level of process capability or organisational maturity. They provide the application of the model-based process assessment. As a result of the process assessment, the current process capability levels and corresponding organisation maturity level are determined, and a roadmap to improve the process capability levels to the higher levels is suggested. Therefore, the processes can be improved by following the roadmap.

This approach has widespread adoption in the software engineering domain to appraise and improve process competence, for example, CMMI [16] and ISO/IEC 330xx series [12]. They have demonstrated their applicability and usability in software organisations worldwide by providing tangible benefits, including expense savings, improved process quality, predictable and consistent process outputs, and increased employee productivity. The success of this approach in the software engineering domain inspired researchers and scholars in customising this approach into emerging domains. However, adopting a process capability maturity approach to define and assess data science from a multidisciplinary perspective for improving organisational capabilities in the data-driven organisation still poses a critical research gap in practice and academic research.

2.3 | Related works

The existing literature is strikingly limited in the data science and data-driven domains. There are only a handful of studies grounded on investigating organisational challenges associated with the successful transition to a data-driven organisation. To identify these existing studies, we performed a literature review in Web of Science (WoS) and Scopus databases with the following keywords: *('data-driven' OR 'data science' OR 'business intelligence') AND ('maturity model' OR 'capability model' OR 'assessment model').* The search results are documented in a spreadsheet to compare and merge duplicated studies. We retrieved 86 studies from WoS and 152 studies from Scopus databases. However, 66 of these studies appeared in both of the databases. As a result, 172 unique studies are initially retrieved to review. Then, we reviewed and evaluated resulting studies according to the following inclusion criteria: (1) published in a conference proceeding, book chapter, or in a journal to signify an academic approach, (2) published with the English language, (3) proposed a capability or a MM for the data-driven organisation, and (4) investigated the organisational capabilities of a data-driven organisation and applicable across all sectors. We also reviewed references and citations of the selected papers to extend literature review results. As a result, we determined only nine relevant studies in the scope of this research after the review process, as detailed in Table 1.

The ISO/IEC 33004 [26] denotes that a capability MM and its assessment results should satisfy the following criteria: *'complete, clear, unambiguous, objective, impartial, consistent, repeatable, comparable, and representative'*. To this end, we evaluated the existing studies according to this set of criteria by following the rating scale defined in ISO/IEC 33002. In these evaluations, we first examined existing studies to determine to what extent they included organisational processes and capabilities of a data-driven organisation to evaluate how they propose complete, impartial, representative, and consistent models. We also investigated the details and granularity of their processes and practice definitions, as well as explanations of the assessment methodologies and measurement attributes to evaluate their objectivity, repeatability, and comparability.

There is a growing research interest in data science and data-driven approaches in recent years. However, the existing literature is strikingly limited in leveraging the process capability maturity approach in these domains. The studies M1, M3, M4, and M6, propose a business intelligence MM. However,

TABLE 1 Existing related works

Model ID	Research title
M1 [17]	Assessing organisational business intelligence maturity
M2 [18]	Becoming a data-driven organisation
M3 [19]	Business intelligence maturity: The economic transitional context within Slovenia
M4 [20]	Towards a business analytics capability maturity model
M5 [21]	Towards a global big data maturity model
M6 [22]	Using quantitative analyses to construct a capability maturity model for business intelligence
M7 [23]	How organisations leverage big data: a Maturity model
M8 [24]	Developing a capability maturity model for enterprise intelligence
M9 [25]	Defining analytics maturity indicators: A survey approach

these studies do not specify any comprehensive detail for measuring an organisation's data science maturity objectively. Moreover, they do not develop their models based on an accepted standard, so these models need to be validated across different organisations and industries. The studies M2 and M8 propose conceptual MMs to define the success and enabling factors of data-driven organisation and enterprise intelligence. However, these studies only demonstrate their preliminary results, and they do not propose a complete MM, nor do they specify any comprehensive detail about assessment processes and attributes. The M5 and M7 focus on proposing big data MM, and these studies largely comprise the big data processes. However, there are some limitations in these studies about defining measurement attributes, the objectivity of the assessment methods of the proposed models. Moreover, these studies also do not provide a roadmap and action plan for process capability improvement. Even though the M9 broadly covers the indicators and factors that affect the analytics maturity of organisations, it does not provide any objective assessment method and does not give full details of the model for the application of the proposed model.

There are also some studies in the grey literature related to data science maturity [27–30]. These studies are not developed based on a model or standard, such as CMMI or ISO/IEC 330xx. Even though they focus on assessing the current capability of the data science or big data processes, they do not provide any structured assessment methodology and a roadmap for process improvement. They do not also guarantee an unbiased academic view as they proposed by a consulting company or a technology vendor. Moreover, these studies do not detail the development and validation process, which hinders their adoption in practice.

As the literature review shows, existing studies do not embrace all predefined criteria, and they mainly lack an objective assessment method and measurement attributes defined in a standardised way. Besides, none of the existing models is compatible with any well-accepted structure such as CMMI or ISO/IEC 330xx. Hence, there is a need to define a well-structured, standardised, and consistent process capability MM for the transition to a data-driven organisation. This study aimed to fill this research gap by providing a process capability MM for transition to data-driven organisation based on a well-accepted standard series, ISO/IEC 330xx. The developed model is explained in the following section.

3 | MODEL DEVELOPMENT

The proposed model, DDPCDM, comprises two dimensions; capability and process. The capability dimension, adapted from ISO/IEC 33002 [31], includes the definition of capability levels, process attributes (PA), generic practices, and generic practice indicators. The process dimension includes process definitions of the organisational management processes to spur the transition to a data-driven organisation. This section details the process and capability dimensions of the proposed model, DDPCDM.

3.1 | Process dimension

The process dimension consists of five critical organisational processes: change management, skill and talent management, organisational learning, strategic alignment, and sponsorship and portfolio management based on findings from the existing literature. The existing studies were reviewed and analysed by six domain experts in data science, digital transformation, process improvement, and information systems to understand the importance and value creations of organisational processes in the transition to a data-driven organisation. The domain experts included authors, and industry participants that work are senior data scientists and a head of the digital transformation department. The domain experts first discussed the existing processes in the literature, and then a brainstorming session was conducted to propose and examine additional processes that may be included in the proposed model. As a result of the analyses, discussion, brainstorming, and judgements of the domain experts, the main constructs of the DDPCDM were finalised. The processes and their corresponding references are detailed in Table 2. In the proposed model, we structurally define and evaluate these processes to guide organisations for successfully implementing and adopting data science and, accordingly, the transition to a data-driven organisation. These processes are defined based on the requirements outlined in ISO/IEC 33004. A sample process definition for sponsorship and portfolio management is given in the Appendix Table A1.

3.1.1 | Change management

Change management is continuously adapting an organisation’s structure, culture, and management capabilities against the demands of becoming a data-driven organisation. The most significant adoption barriers organisations face in becoming a data-driven organisation are managerial and cultural, which necessitates change management in an organisation [6]. The top management should lead these cultural and managerial problems by redefining organisational structure, leadership, and business processes. Top-management support plays a crucial role in initiating organisational transformation for creating data-driven culture across the organisation [32]. As data science is a multidisciplinary domain, the people involved in the data science process life-cycle generally do not share the same skills and terminology to serve as a baseline of

TABLE 2 Processes and their corresponding references

Process	References
Change management	[17, 18, 20, 21, 23]
Skill and talent management	[17, 20, 21, 23]
Organisational learning	[23, 29, 30]
Strategic alignment	[17–22]
Sponsorship and portfolio management	[17, 27–30]

communication. Thus, organisations should be restructured to share a common data-driven culture and to define an efficient and effective communication channel among data scientists, software developers, analysts, testers, stakeholders, and top-executive managers to support collaboration and interaction in operating data science. To sum up, the change management process covers evaluating how organisational policies and directives are established and maintained to restructure and align the organisation in transition to the data-driven culture. As a result of the successful implementation of this process, organisations understand the scope and desire to change, assess stakeholders' and employees' readiness and willingness for change, identify and deploy action plans to motivate stakeholders and employees, and increase their participation in change management and monitor and sustain organisational changes.

3.1.2 | Skill and talent management

The skill and talent management process focuses on acquiring, training, and integrating skills and talents to build the right multidisciplinary team for data science. Businesses need to reconfigure and train their human resources according to rapidly changing business environments and technology solutions to sustain competitive advantage. Thus, they need to develop a unified human resource management strategy to determine how required people skills and competencies are identified, developed, or acquired and to evaluate the performance of candidates and employees against the defined performance criteria to meet organisational needs. Another critical problem in human resource management is training employees in the organisation about the basic data science principles and methodologies to include them in the analytical decision-making process [1]. The skill and talent management process evaluates how qualified human resource is acquired, integrated and trained to build a complementary data science team of multidisciplinary skills. This process will help organisations develop a strategy for management to identify necessary skills and competencies in building a multidisciplinary data science team, developing training programs to maintain and improve data science skills of existing staff, and evaluating and rewarding staff job performance.

3.1.3 | Organisational learning

Organisational learning can be defined as creating, documenting, storing, and sharing individuals' know-how and past-experiences within an organisation [33]. The organisational learning process positively impacts the organisations' strategic performance [33]. Businesses need to integrate the knowledge and experience of individuals into an organisational knowledge base to obtain sustainable business and strategic performance [34]. To initiate a successful transition to a data-driven organisation in a standardised, repeatable, and consistent manner, organisations need to effectively manage their know-how and share it with related stakeholders to make output work products more reliable. The purpose of the organisational learning process is to evaluate how the organisation documents, stores, manages, and shares the experimental knowledge to make the output work products more reliable. As a result of the successful implementation of this process, organisations develop an organisational management roadmap, identify and classify the source of information to organise and contextualise information into knowledge and assess, update or retire their organisational knowledge assets.

3.1.4 | Strategic alignment

The strategic alignment process aims to establish a strategic direction and ensure a common understanding of organisational goals and strategic business directions. Organisations start their journey to become data-driven organisations by first establishing their data science strategy and vision [35]. However, organisations also need to align their business and data science strategies to stimulate their transition from intuition-driven to a data-driven organisation and improve their profitability and reduce investment risks [36]. This also allows organisations to leverage data science as their core competency and skill. Accordingly, the strategic alignment process evaluates how organisations align their business and data-driven organisation strategies, directions, requirements, and short and long-term goals. This process enables organisations to understand their business environment and directions, determine their target data science capabilities in line with organisational vision, and establish and maintain a strategic plan and roadmap to drive alignment among business, data science, and IT units.

3.1.5 | Sponsorship and portfolio management

The sponsorship and portfolio management process aims to ensure that financial resources and assets are used effectively and efficiently to achieve organisational strategy, goals, and business directions to become a data-driven organisation. Moreover, sponsorship and portfolio management allow organisations to grasp optimal gain from strategically aligned investments at an affordable cost with a known and acceptable risk level. This process evaluates whether financial planning and controlling are managed in an organisation to employ financial resources for efficiently funding projects to support becoming a data-driven organisation. This also includes developing sponsorship and funding models, evaluating and monitoring ongoing funded projects to decide whether to continue or terminate funding. As a result of successful implementation of this process, organisations execute the strategic direction set for their investments in line with organisational vision, consider and evaluate different sponsorship and funding models and options to support and maintain their portfolios, and monitor, optimise and evaluate projects in their ongoing portfolios to make adjustments according to their changing business environment and priorities.

3.2 | Capability dimension

The process capability level assessment describes the organisation's competency relative to a particular process. The measurement framework provided by ISO/IEC 33002 [31] is utilised. The proposed model, which is delineated in Figure 1, has six capability levels, and each level has its own PAs, defined as a measurable property of process capability. A capability level represents a well-defined set of PAs that provide a significant improvement in the capability of a process. The defined PAs in each level addresses the specific needs of the capability levels, and they progress through the improvement of the capability of any process. Each process is required to be at least a 'Largely Achieved (L)' for the corresponding PAs for each capability level and 'Fully Achieved (F)' for any lower capability levels PAs.

The capability levels defined in the ISO/IEC 33002 measurement framework from level zero to level five have been developed to be appropriate universally to all processes except for Level 1 (performed) where the observable indicators are different for each process, while all the PAs from Levels 2 to 5 are common for all processes. In the scope of this study, the definitions of five organisational processes (change management, skill and talent management, strategic alignment, organisational learning, and sponsorship and portfolio management) are developed, including Level 1 process performance indicators as outcomes, base practices, and work products. Thus, the organisational data drivenness processes capability level can be assessed based on ISO/IEC 330xx owing to these developed process definitions.

Level 0 *Incomplete:* In this capability level, the organisation does not fully or largely perform base practices. In other words, the organisation does not have any initiative to start the transition from intuition-driven to a data-driven organisation.

Level 1 *Performed:* The organisation largely or fully performs the base practices defined in the process definition, but most of these processes are performed ad hoc. In other words, there is no consistent way of performing organisational management processes in the transition to a data-driven organisation. At this capability level, the processes are unpredictable, poorly controlled, and reactive.

Level 2 *Managed:* The base practices defined in the process definition are fully performed. The organisation starts to recognise the business value of data-drivenness and starts focussing on improving process performance by defining performance objectives for each process. Moreover, organisations are expected to identify, manage, and control work products of each process for performing processes consistently.

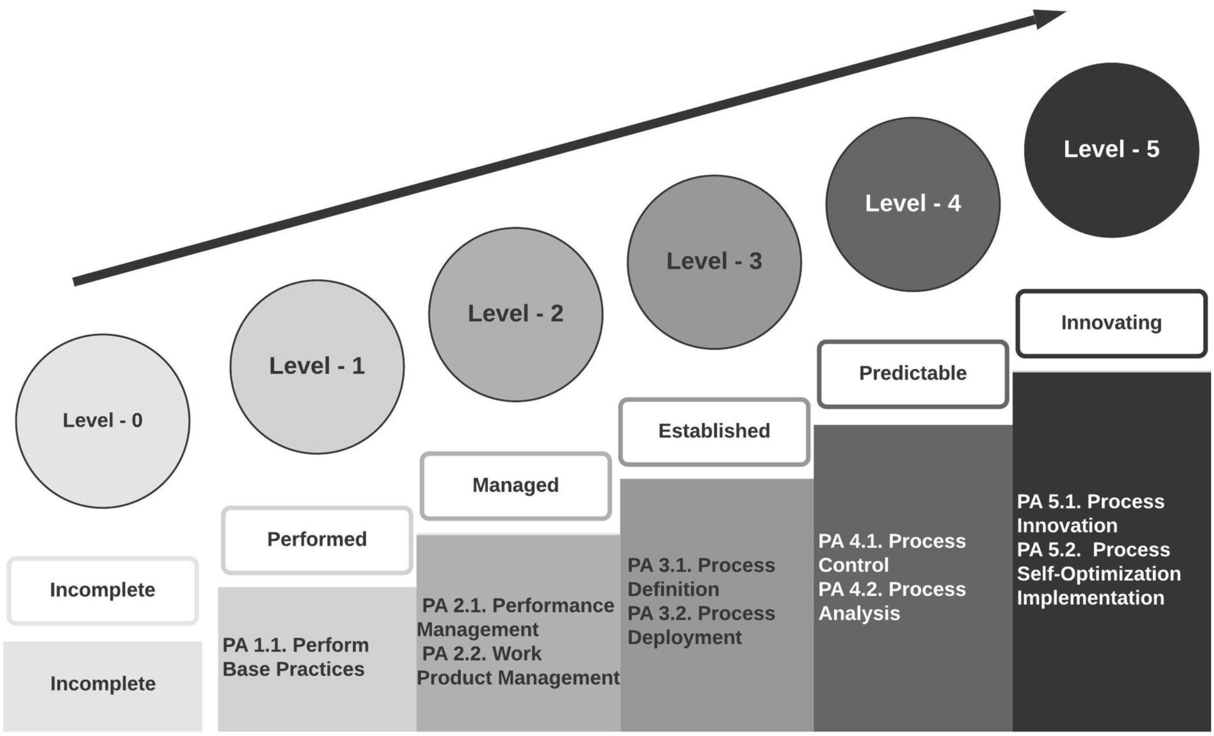

FIGURE 1 Capability levels of the proposed model (adapted from ISO/IEC 33002)

Level 3 *Established:* At this level, organisations are expected to perform and maintain processes in a standardised way by defining and controlling each process. At this capability level, the defined processes are recognised as major skills in the transition to a data-driven organisation.

Level 4 *Predictable:* The organisation begins managing its processes through the quantitative data that describes the performance and variations in performing best practices, which are reduced by controlling and analysing processes. A controlled process is planned, performed, and monitored to achieve a quantitatively managed process. To this end, statistical and quantitative measures are collected at this level to control and monitor the process against the plan and to take appropriate corrective action when it is needed. At this capability level, organisations completely embrace the transition from intuition-driven to data-driven organisation.

Level 5 *Innovating:* In this capability level, the organisation fully performs defined PAs, starts self-learning from collected measures to improve the effectiveness of data-drivenness continuously. The business model is evolving into an innovative structure with the gained insights from data science. Moreover, organisations start creating competitive differentiation in their marketplace through innovation.

4 | MATERIALS AND METHODS

This section details the design of the multiple-case study and explains utilised data collection, analyses, and validation methods in case studies.

4.1 | Multiple-case study design

In this study, we conducted a multiple-case study to evaluate the applicability and usability of the proposed model. We followed the template proposed by Yin [37] in designing this multiple-case study in Table 3.

4.2 | Data collection

The main sources of evidence of this multiple-case study are unstructured assessment interviews, audits, organisational documents, and observations. The assessment team, including the authors, planned the assessment, gathered and validated data by following ISO/IEC 33020: Process Measurement Framework for Assessment of Process Capability. The assessment team has experience in management, digital transformation, process improvement, and data science domains, and two of the team members also have competency in applying practices and guidelines provided by ISO/IEC 330xx.

We have conducted process capability assessments in two different organisations operating in different sectors and having different sizes. The first organisation is an industrial company and produces chemical products. It has operational, sales, and data science units around the world. They mainly utilise the data science to increase their revenues, customer satisfaction and minimise operational risks and costs. In this organisation, we held a three-hour assessment meeting with the data scientists, IT manager, and stakeholders that include data engineers and business analysts to collect data and a 2-h follow-up interview to discuss the proposed model and its results. We will describe this case as Case 1 for the rest of the paper.

The second case operates in the mining industry, with more than a thousand employees. We will mention this case as Case 2 for the purpose of confidentiality. In this case, we held a 2-h assessment meeting with the executive managers that are mainly accountable for the transition to a data-driven organisation to collect data and evidence and a 2-h follow-up interview to discuss the applicability and usability of the model and assessment results.

In both organisations, we collected data from multiple sources, including assessment interviews, organisational strategy documents, and observations. Organisational structure, hierarchy, and intra-communication channels among managers

TABLE 3 Multiple case study design

Define the objective of the research	The main objective of this case study research is to assess the applicability and usability of the DDPCDM
Define the research questions (RQs):	The RQ of this research is as follows: - How applicable and useful is proposed DDPCDM to be used with the purpose of identifying the current process capability levels for the transition to a data-driven organisation and providing guidelines for improvement?
Determine case study design type	This is a multiple-case study research as conducted literal replication of the same case-study at different organisations
Determine the measures used in the case study	The main measures of this multiple-case study are the capability levels of change management, skill and talent management, strategic alignment, organisational learning, and sponsorship and portfolio management processes
Define data collection and limitations	In this research, we collected data from different evidence sources, including assessment interviews, organisational documents, audits, and observations, to evaluate processes in a reliable and objective manner
Evaluate objectivity of the judgements:	To ensure objectivity and reliability of the analysis of the collected data, we followed the ISO/IEC 33002 [31] standard, which defines a set of standards to rate PAs, plan assessment, validate data, and rate processes

and employees were also investigated. The assessment interviews were also recorded during the meetings with the consent of participants.

The main reasons to select these organisations as case-studies are their endeavours to initiate transformation from intuition-driven to a data-driven organisation, and they have experience in data science. In both case studies, the interview participants are mainly responsible for top management, data science, human resource management, and information and communication technologies. Before conducting interviews, the scope of our research and proposed model, including process and capability dimensions and the assessment method, were presented to the participants in detail.

4.3 | Data analysis and validation

In the analysis of collected data from the multiple-case study to evaluate process capabilities of participant organisations in an objective and unbiased manner, we utilised the rating scale, assessment guidelines, and recommendations provided by ISO/IEC 33020 [38].

The case study researches inherently comprise some validity threats in collecting, analysing, and validating the data. These potential threats should be identified and resolved in the planning phase. To this end, we investigated the potential validity threats that may arise in this multiple case study in four categories according to the study of Yin [39] as follows: the possible *Construct Validity* threat for these case studies is avoiding conflicts between researchers and practitioners and identifying the correct source of evidence to gather subjective judgements for eliminating bias. The assessment team collected data from multiple sources of evidence, including face-to-face interviews, organisational documents, observations, and audits, to gather subjective judgements. Moreover, the assessment team utilised the 4-point ordinal rating scale provided by ISO/IEC 33020 to mitigate subjectivity threat as much as possible. The rating scale includes not achieved (N), partially achieved (P), largely achieved (L), and fully achieved (F) values.

To mitigate *Internal Validity* threats, the assessment team developed a detailed and diverse question set for each process, base practice, and generic practices to collect evidence at different granularity levels. As we followed a well-established ISO/IEC 33020 standard in model development and assessment processes, the contradictions between researchers and case study participants were also avoided.

External Validity and *Reliability* threats question the generalisability of the case study results and evaluate if the study is valid in its own setting or applicable in other settings as well. To mitigate these threats, the assessment team employed a literal replication logic of the assessment process with two different organisations. We selected participant organisations in different sectors and sizes to increase the generalisability of the model and the reliability of the case study results.

The process assessment plan is depicted in Figure 2. The assessment process started with documentation of the assessment plan that includes defining the assessment team, interview schedule, delivery dates, and outputs. The assessment plans were shared with the participant organisations to be approved. Then, we conducted 3-hr semi-structured interviews with participant organisations to collect data, observations, and pieces of evidence to rate PAs. After analysing the collected evidence, the capability levels of the defined processes were determined, and an assessment report, including the current capability level of the assessed processes and a roadmap as well as suggestions to improve process capabilities to the next level, was prepared and shared with the participant organisations.

5 | FINDINGS AND DISCUSSION

In this section, we present the capability assessment results of the change management, skill and talent management, organisational learning, strategic alignment, and sponsorship and portfolio management processes for the case study participant companies. We also detailed the follow-up interviews that aim to discuss and answer the defined RQ about the applicability and usability of the DDPCDM in a multidisciplinary domain. The assessment team rated the defined PAs to determine the processes capabilities for the transition to the data-driven organisation in Case 1 and Case 2 based on the gathered evidence and findings by following the guidelines provided by ISO/IEC 33002 [31] for performing process assessment and ISO/IEC 33020 [38] assessment of the process capability levels.

5.1 | Assessment results: The Case 1

According to the assessment results, Case 1 achieves process capability Level 3 in organisation management processes for a successful transition to becoming a data-driven organisation. The detailed PA ratings and process capability levels are given in the Appendix Table A2, and the assessment results are delineated in Figure 3.

Case 1 has a clear business vision and strategy for data science and transition to a data-driven organisation and makes significant investments in people and change management to initiate a cultural transformation from intuition-driven to a data-driven organisation. The data science and change management endeavours are supported by executive managers. Accordingly, they have a critical budget to align their business direction and becoming a data-driven organisation vision, and accordingly, execute their portfolio. Consequently, they currently have well-established and managed organisational processes for the transition to a data-driven organisation. They can improve their organisational process capabilities to spur the adoption of data science and transition to a data-driven organisation by following the provided suggestions in Table 4.

5.2 | Assessment results: The Case 2

Case 2 achieves process capability Level 2 in sponsorship and portfolio management and organisational learning processes

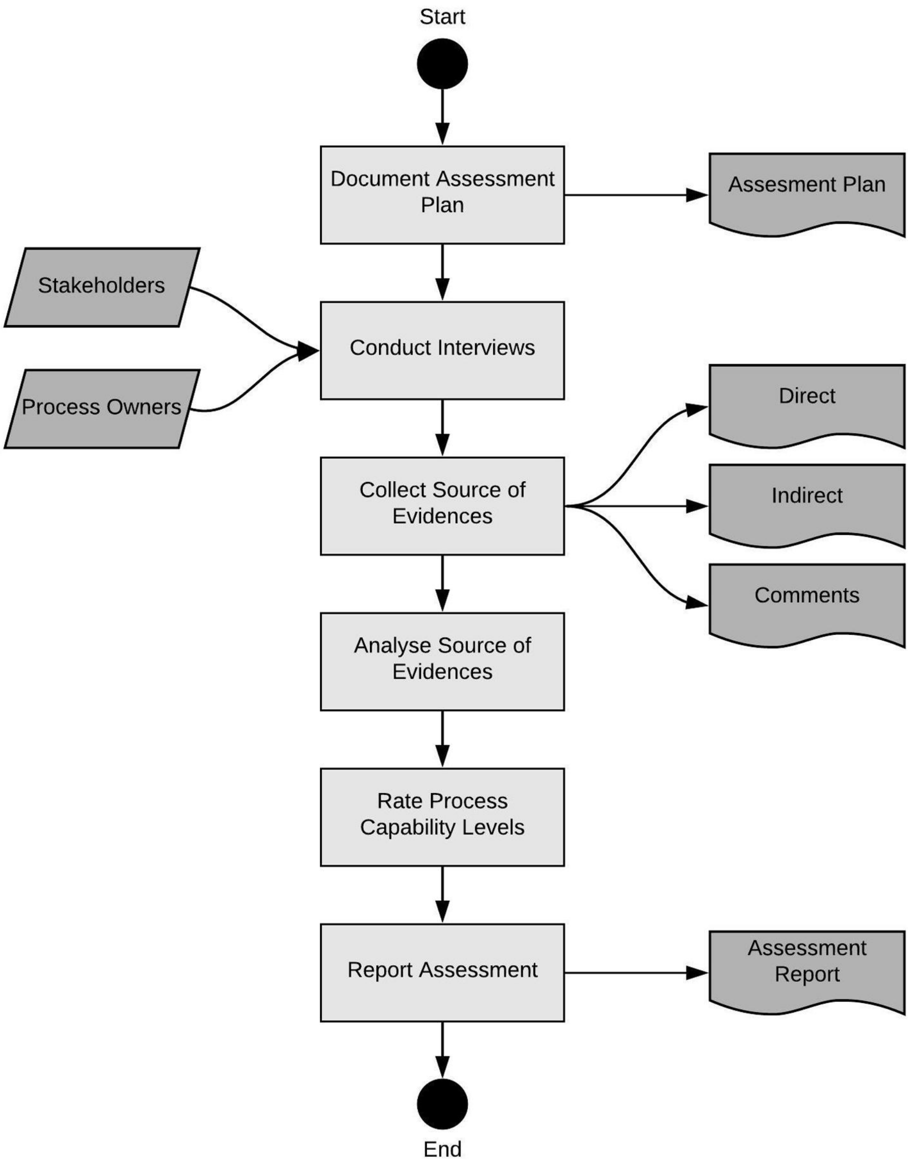

FIGURE 2 Process assessment activities

and capability Level 1 in strategic alignment, skill and talent management and change management processes. The detailed process capability ratings are given in the Appendix Table A3, and the assessment result is delineated in Figure 4.

Case 2 realizes the importance of becoming a data-driven organisation to attain a competitive advantage in their rapidly changing and challenging business market. The sponsorship and portfolio management, and organisational learning processes are clearly defined, managed, and their work products are controlled and performed consistently. However, they perform strategic alignment, skill and talent management, and change management processes in an ad hoc manner. This causes weakly controlled, partial, unpredictable, and reactive process definition and management. This is mainly because they have a limited budget, a small number of employees, and a distributed organisational structure to manage the transition to a data-driven organisation more robustly. The assessment team provided improvement suggestions for each process in the provided assessment report as detailed in Table 5.

5.3 | Discussion

We also conducted follow-up interviews with the same participants after presenting the assessment results to find answers for the defined research question. In these interviews, structured questions which are answered by 5-point-Likert Scale (1: strongly disagree and 5: strongly agree) and open-ended questions, which are defined below, were utilised to discuss the applicability and usability of the proposed model in determining capability levels of the organisational management processes in the transition to a data-driven organisation and providing guidelines and suggestions for improvement of data-drivenness.

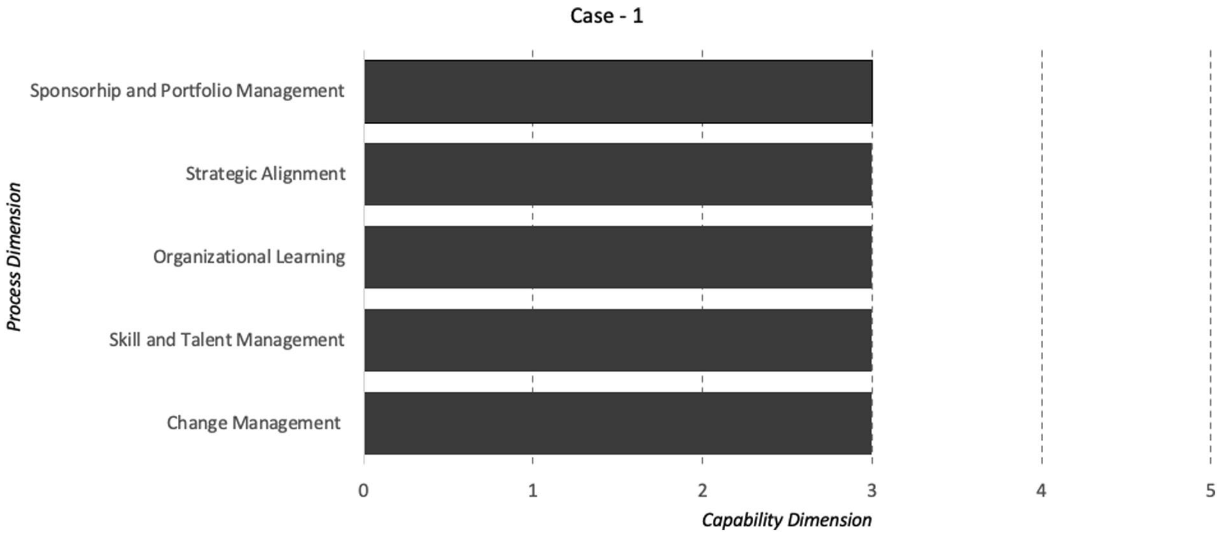

FIGURE 3 Process capability levels of Case 1

TABLE 4 Example improvement suggestions for Case 1

Processes	Example improvement suggestions
Change management	- An interactive communication interface among data scientists, business units, and IT teams can be established to improve communication and collaboration - Assign and communicate roles, responsibilities, and authorities to robustly perform the change management process - Collect and analyse data about the performance of the change management process to demonstrate its applicability, suitability, and effectiveness - Define key activities, milestones, work product templates, and interaction, among other processes
Skill and talent management	- Identify and evaluate required skills and competencies to be provided or improved through training - A training plan can be established to manage skills and talents in performing their assigned roles - Determine the sequence and interaction among processes to work as an integrated system and improve efficiency and effectiveness in processes - Key performance indicators and success measures can be determined to monitor the effectiveness and suitability of this process
Organisational learning	- Learning and knowledge assets can be assessed according to their value to the organisation for validating and ensuring their appropriateness to the changing data science, business, and technology environment - Identify the roles and competencies to robustly performing the organisational learning process
Strategic alignment	- Monitor alignment process and identify shortfalls by collecting feedbacks about strategy and management processes - An agile road-mapping approach can be utilised to discuss changing business environment and data science and revise alignment objectives as needed - Resolving issues arising from work product reviews should be tracked systematically
Sponsorship and portfolio management	- Research and assess potential sponsorship and funding options - Develop sponsorship proposal in line with data science vision by demonstrating outcomes and clarifying the benefits to the organisation - Develop success metrics to evaluate sponsorship and funding proposals - Regularly monitor and report the performance of the available portfolio

- Are measuring the capabilities of organisational management processes for the transition to a data-driven organisation and obtaining a guideline and suggestions for process capability improvement useful? (5-point Likert Scale): Median: 4
- Do you think that applying provided suggestions will improve the process performance? (5-point Likert Scale): Median: 4
- Do you think that language and terminology in the assessment interviews are easy to understand? (5-point Likert Scale): Median: 4
- Is there any missing item in the guideline for the improvement list? (Open-ended): *'No'*.
- Is there any information you want to add in the process definitions? (Open-ended): *'No'*.

The participants declared that provided suggestions and guidelines are applicable and useful to improve their current capability of the organisational management processes in becoming a data-driven organisation, and they will apply these suggestions in their organisations. They also indicated that the language and terminology used in the questions were easy to

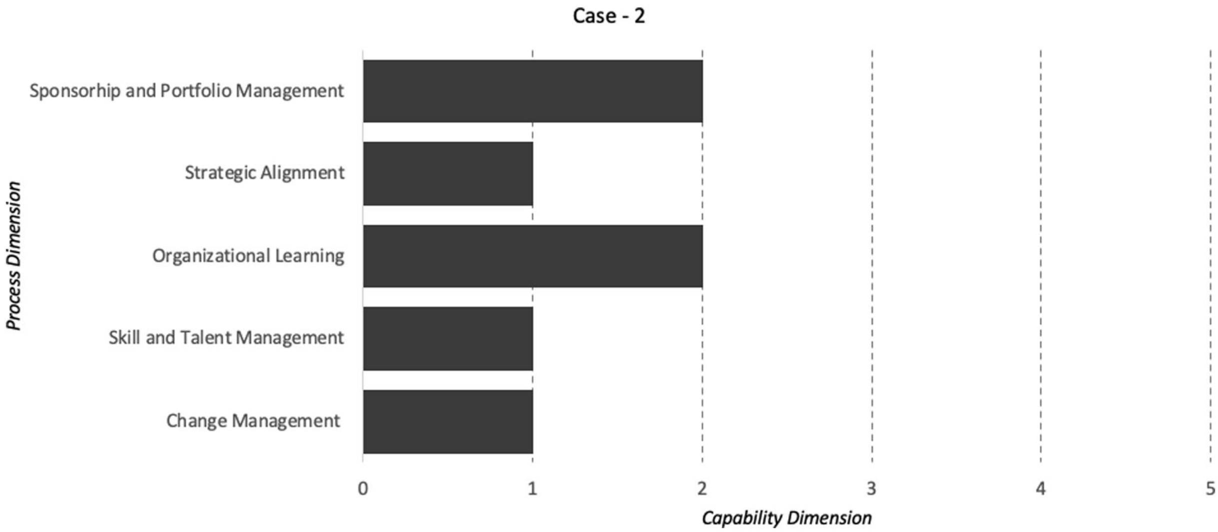

FIGURE 4 Process capability levels of Case 2

TABLE 5 Example improvement suggestions for the Case 2

Process	Example improvement suggestions
Change management	- Workshops and meetings can be conducted to discuss and determine the scope and impact of the change management - Evaluate the stakeholder readiness and willingness to change - An action plan and incentives can be planned to motivate employees and increase their participation to improve the effectiveness of the change management process - Objectives and key performance indicators can be defined to monitor and evaluate the performance of the process
Skill and talent management	- Determine available data science employee skills and define required skills to achieve the organisational vision - Training and skill development programs can be developed to maintain the skills and competencies of the employees to fulfil their responsibilities - Regular assessment reviews can be conducted to evaluate the effectiveness of the training programs and the evolution of the available talents.
Organisational learning	- Internal and external information sources can be classified and categorised based on a set of predefined criteria - Relationships among information sources and elements can be defined - Transfer knowledge assets to employees based on effective organisational learning methods
Strategic alignment	- A gap analysis should be conducted to determine existing capabilities and define target data science capabilities in line with organisational vision - A strategic plan and roadmap should be established to drive alignment between business, data science, and IT units - The existing business model should be aligned with the becoming a data-driven organisation vision to achieve business objectives - Communicate and collect feedback from all employees and stakeholders throughout the organisation about the strategic alignment process - Identify, document, and control the work products
Sponsorship and portfolio management	- Establish and maintain a portfolio by selecting proposals to be invested for internal investments - Identify, prepare, and make available financial resources to manage the portfolio - Human and IT resources should be allocated to manage and execute the portfolio - Define the requirements for documentation and control of the work products

understand. Moreover, according to the participants, the processes are extensively defined to cover the important practices of data-driven organisations from a holistic multidisciplinary perspective, and suggestions for process improvement were not deficient. Consequently, according to the answers of the follow-up interview participants, the research questions are answered; the proposed DDPCDM is applicable and useful with the purpose of identifying the current organisational management processes in the transition to the data-driven organisation, and it also provides valuable guidance to move these processes to the next capability level.

6 | CONCLUSIONS AND FUTURE WORK

Data science grasp the potential to improve operational performance, data-driven decision-making capabilities of business units and attain a competitive advantage in their businesses. As data science is a multidisciplinary domain, it should be managed at the organisational level to manage and coordinate data science endeavours throughout the organisation. However, there is a limited understanding of how organisations can measure and improve their data science capabilities to spur the transition to a data-driven organisation due to a lack of a comprehensive roadmap with a structural approach like the PCMM. To this end, this study investigates organisational management processes of data science for a successful transition to a data-driven organisation and proposes the DDPCDM based on a well-accepted standard, ISO/IEC 330xx. The proposed model, DDPCDM, supports organisations in determining their current organisational data science capabilities in the transition to the data-driven organisation and provides a comprehensive roadmap to improve capability levels in a structured way.

The main contributions of this study are (1) validating the need for a process capability MM for the transition to a data-driven organisation by providing a review of the available models from a specific data-driven organisation perspective; (2) closing this research gap through the development of the DDPCDM based on ISO/IEC 330xx standard series; (3) conducting a multiple-case study to validate the applicability and usability of the proposed model. According to the findings of the multiple-case study, the proposed model is applicable and usable to identify the current state of an organisation's management capabilities in the transition to the data-driven organisation and provide useful suggestions and roadmaps for improvement.

Despite its contributions, this study has some limitations that we need to focus on in future studies. The main limitation of this research is the generalisability of the case study in small and medium-sized enterprises. In future studies, we plan to conduct a literal replication of the multiple-case study with organisations in different industries and sizes to validate the generalisability of the proposed model.

CONFLICT OF INTERESTS

The author declares that there are no conflict of interests.

ORCID

Mert O. Gökalp https://orcid.org/0000-0002-4812-7989

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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APPENDIX A

TABLE A1 Sponsorship and portfolio management process definitions according to ISO/IEC 330xx

Process name	Sponsorship and portfolio management
Process purpose	The purpose of the sponsorship and portfolio management process is to ensure that organisations grasp optimal gain from strategically aligned investments at an affordable cost with a known and acceptable level of risk
Process outcomes	1) As a result of successful implementation of this process:
	Strategy, vision, and policies are identified for sponsorship and portfolio management
	Sponsorship and funding models for internal and external investment options are developed
	Evaluation criteria and metrics for sponsorship and funding models are developed
	Business cases to achieve the strategic vision are developed for sponsorship and funding proposals
	Internal funding portfolio is established, monitored, and maintained
	Necessary financial, human, and IT resources are allocated to execute funded projects
	Ongoing funded projects are monitored and evaluated to decide whether continue or terminate funding
Base practices (BPs)	**BP1: Establish and maintain a strategy, vision, and policies for sponsorship and portfolio management.** Establish and maintain a strategy and policies for sponsorship and portfolio management to manage financial resources. [Outcome: 1]
	BP2: Determine availability and sources of sponsorship and funding models. Develop funding models, funding options, and research and assess potential sponsorship and funding options. Moreover, develop criteria and metrics to evaluate sponsorship and funding proposals. [Outcomes: 2, 3]
	BP3: Develop business cases for sponsorship and funding. Develop business cases to demonstrate outcomes and clarify the benefits of sponsorship proposals. [Outcomes: 4]
	BP4: Categorise and prioritise project proposals to determine portfolio in line with organisational vision. Categorise and project prioritise proposals according to defined evaluation criteria to determine portfolio. [Outcome: 4]
	BP5: Establish and maintain portfolio. Establish and maintain a portfolio by selecting proposals to be invested for internal investments. Allocate internal financial, human, and IT resources to manage and execute selected investments. [Outcomes: 5, 6]
	BP6: Monitor, optimise and evaluate the ongoing portfolio. Monitor, optimise, and evaluate ongoing investments according to achieve strategic objectives of the organisations and to determine whether continue or terminate funding. [Outcome: 7]
Output work products	Organisational strategy and vision. [Outcomes: 1, 2, 3, 4]
	Criteria for categorising investments. [Outcome: 1]
	Criteria for evaluation investments. [Outcome: 1]
	Possible sponsorship and funding models and options. [Outcomes: 2, 3]
	Business case. [Outcome: 4]
	Prioritised and categorised proposals. [Outcome: 4]
	Funding portfolio. [Outcome: 5]
	Financial, human, and IT resources. [Outcome: 6]
	Funding performance and success metrics. [Outcome: 7]

TABLE A2 Assessment results of the Case 1

	Level 1	Level 2		Level 3		
	PA 1.1.	**PA 2.1.**	**PA 2.2.**	**PA 3.1.**	**PA 3.2.**	**Result**
Change management	F	F	F	F	L	Level 3
Skill and talent management	F	F	F	L	L	Level 3
Organisational learning	F	F	F	L	L	Level 3
Strategic alignment	F	F	F	L	L	Level 3
Sponsorship and portfolio management	F	F	L	L	L	Level 3

N: Not Achieved, **P:** Partially Achieved, **L:** Largely Achieved, **F:** Fully achieved

TABLE A3 Assessment results of the Case 2

	Level 1	Level 2		Level 3		
	PA 1.1.	**PA 2.1.**	**PA 2.2.**	**PA 3.1.**	**PA 3.2.**	**Result**
Change management	L	–	–	–	–	Level 1
Skill and talent management	F	P	P	–	–	Level 1
Organisational learning	F	L	L	N	N	Level 2
Strategic alignment	L	–	–	–	–	Level 1
Sponsorship and portfolio management	F	L	L	P	N	Level 2

N: Not Achieved, **P:** Partially Achieved, **L:** Largely Achieved, **F:** Fully achieved