A Process Mining Success Factors Model

Azumah Mamudu[1[0000-0003-0897-5112]], Wasana Bandara[1[0000-0003-2785-7859]], Moe T. Wynn[1[0000-0002-7205-8821]] and Sander J.J. Leemans[1[0000-0002-5201-7125]]

[1] Queensland University of Technology, Brisbane, Australia
azumah.mamudu@hdr.qut.edu.au,{w.bandara,m.wynn,s.leemans}@qut.edu.au

Abstract. Process mining – a suite of techniques for extracting insights from event logs of Information Systems (IS) – is increasingly being used by a wide range of organisations to improve operational efficiency. However, despite extensive studies of Critical Success Factors (CSF) in related domains, CSF studies of process mining are limited. Moreover, these studies merely identify factors, and do not provide essential details such as a clear conceptual understanding of success factors and their interrelationships. Using a process mining success model published in 2013 as a conceptual foundation, we derive an empirically supported, enhanced process mining critical success factors model. Applying a hybrid approach, we qualitatively analyse 62 process mining case reports covering diverse perspectives. We identify nine process mining critical success factors, explain how these factors relate to the process mining context and analyse their interrelationships with regard to process mining success. Our findings will guide organisations to invest in the right mix of critical success factors for value realisation in process mining practice.

Keywords: Process mining, success factors, process mining success, process mining impact, case reports.

1 Introduction

Process mining (PM) is a research discipline focused on extracting knowledge from event logs readily available in today's business systems to discover, monitor, and improve real processes [1]. Organisations can utilise PM techniques to achieve operational excellence and organisational resilience[1]. In the past decade, the adoption of process mining has expanded considerably [2], evidenced by many use cases reported in industry (e.g. [3]) and academia (e.g. [4]), especially in sectors such as auditing [5], insurance [6], and healthcare [7]. The field has also significantly matured with enhanced capabilities in tools and techniques [8].

According to Gartner[2], the global process analytics market size will grow at a Compound Annual Growth Rate of 50% from US$185 million to US$1.42 billion between

[1] https://www.processexcellencenetwork.com/process-mining/articles/why-the-real-value-of-process-mining-lies-in-simulation. Accessed 10th June 2021
[2] https://www.gartner.com/en/documents/3991229. Accessed 5th June 2021

2018 and 2023. Deloitte's[3] Global Process Mining Survey indicated that 67% of the respondents had started implementing process mining. 87% of non-adopters were considering pilot runs, 83% of "global scale users" intended to expand process mining use, and 84% believed that process mining delivered value to their organisation.

The ongoing growth in PM adoption necessitates further investigation of process mining success, particularly to uncover the complexity and diversity of factors that influence successful project implementation [9]. In this study, a PM initiative is considered a success if it is *effective* (fulfils its objectives) and *efficient* (the relevant activities are completed with the allocated resources such as time, effort and budget). Traditionally, PM research has given more attention to developing tools and techniques [10, 11], with minimal attention to the organisational aspects of PM. This has left areas such as process mining success largely unexplored. Academic discourse on the organisational benefits of process mining is emerging; for example, vom Brocke, Jans, Mendling and Reijers [11] call for research to identify considerations for the adoption, use, and effects of process mining.

One widely used approach in understanding what factors are necessary for success is the study of Critical Success Factors (CSF), originally introduced by Rockart [12]. While many CSF studies exist in related domains, there are very few in the process mining field. These process mining CSF studies identify success factors (e.g., [4]) but provide very little or no contextual interpretation of these factors, their interrelationships, or insights into their level of criticality for organisational success. It has been argued that mere identification of factors, variables and practices without a context-specific understanding of the application of these factors or their interrelationships is ineffective for enabling project success [13]. A better understanding of how CSFs interrelate to directly or indirectly influence success and in what manner they vary in importance over time is argued as essential [14].

This study aims to provide a rich understanding of process mining CSFs in practice. We analysed 62 published case reports to identify and describe CSFs pertinent to the process mining context. To avoid the criticism often received by CSF studies, we sought to derive a PM CSF model that goes beyond a mere list of factors and provides evidence-based interrelationships between these success factors. Such a model provides deeper insights into the combined and integrated influence these CSFs have on attaining PM success.

The subsequent sections of our paper are structured as follows: Section 2 discusses the related work on critical success factors in process mining and related domains. Section 3 summarises our study methodology. Section 4 provides the re-specified process mining success factors and contextual explanations. Section 5 presents an enhanced PM success factors model and discusses identified interrelationships, and Section 6 concludes the paper. The URL and details of Supplementary Material (an overview of the case reports (A), example quotes from case reports (B) and supporting case evidence for interrelationships (C)) are provided in the Appendix.

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[3] https://www2.deloitte.com/de/de/pages/finance/articles/global-process-mining-survey-2021.html. Accessed 15th June 2021

2 Related Work

CSF studies initially gained significant attention after Rockart [12] highlighted their relevance in influencing the information needs of top executives [15]. CSFs are defined as “the limited number of areas in which results, if they are satisfactory, will ensure successful competitive performance for the organisation” [12]. Since then, this concept has been adopted in diverse project-related contexts.

Despite the proliferation of CSF studies, they have been criticised [14] for providing mere lists of factors and lacking a deeper contextual understanding of how these factors may vary in importance over time [13]. Without a contextual understanding, a mere list of factors is ineffective in predicting success or designing interventions that enable success [13]. Fortune and White [14] also argue that CSF studies often do not account for factor interrelationships, although these are “at least as important as the individual factors” [14]. Thus, there is a clear push for CSFs to go beyond lists of factors and provide deeper insights.

CSF studies have been conducted in related domains such as BPM and data mining (e.g., [16] and [17]). Alibabaei, Bandara and Aghdasi [16] propose a holistic BPM success factors framework with nine CSF and related sub-constructs and how they achieve success. The Big Data Analytics (BDA) framework by Grover, Chiang, Liang and Zhang [18] provides a detailed analysis of moderating factors, capabilities, and value realisation potentials for transforming BDA investments into value. Most CSF studies in BPM and data mining hardly explore CSF interrelationships, though this is a commonly criticised aspect of CSF studies [13]. While insights from related domains are valuable, context specificity is essential for a CSF study to be beneficial [13], which points our attention to PM CSF studies.

In the process mining domain, there is recent work highlighting the need to carefully examine the value proposition of process mining (e.g. [11]). However, to the best of our knowledge, very few research studies (e.g., [4] and [19]) explore process mining CSF. The business process mining success model by Mans, Reijers, Berends, Bandara and Prince [19] is the first study on process mining success factors. Published in 2013, it identifies three success measures (model quality, process impact and project efficiency) and six success factors (project management, management support, structured process mining approach, data and event log quality, resource availability and process miner expertise), empirically supported via four case studies. However, the Mans, Reijers, Berends, Bandara and Prince [19] model does not explore CSF interrelationships or their criticality. Syed, Leemans, Eden and Buijs [4] identify four enabling factors for process mining success at the early stages of PM adoption within an organisation: actionable insights, confidence in process mining, perceived benefits, and training and development. However, this study is based on a single case organisation and is specifically focused on the PM adoption stage, thus questioning its generalisability and broader applicability.

The Deloitte Global IT and business executives survey identified 19 PM success factors. The five key factors reported were the need for a cross-departmental alignment between IT and business, good data quality and transformation, clear targets and the value hypothesis, the availability of dedicated resources towards process mining, and the need for leadership commitment. However, as the respondents were all IT and business executives, the results only explain CSF from a high-level *organisational* perspective with little insight into specific process mining *project* contexts.

In summary, existing CSF literature in process mining, at best, provides a list of factors. While some try to contextualise, they focus on a single case study organisation at the PM adoption stage; others explain these factors only from a high-level perspective. Potential interrelationships or the level of criticality of the factors are never explored. We aim to address this gap with our re-specified PM CSF model.

3 Study Method

Our study applies a hybrid approach to thematic analysis (i.e. using both inductive and deductive coding) of publicly available process mining case reports, conducted across three phases as outlined below:

Phase 1 focused on deriving a preliminary conceptual base. Given that the Mans, Reijers, Berends, Bandara and Prince [19] model is the most widely known model for process mining, we adopted its CSFs as our a-priori base, as summarised in Table 1.

Table 1: PM success factors from Mans, Reijers, Berends, Bandara and Prince [19]

Construct	Definition
Management Support	The involvement and participation of senior management, and their ongoing commitment and willingness to devote necessary resources and time of senior managers to oversee the process mining efforts.
Project Management	The management of activities and resources throughout all phases of the process mining project to obtain the defined project outcomes.
Resource Availability	The degree of information available from the project stakeholders during the entire process mining analysis.
Process Miner Expertise	The experiences of the person conducting the mining, in terms of event log construction, doing process mining analysis and knowledge of the business processes being mined.
Structured Process Mining Approach	The extent to which a process miner uses a structured approach during the entire process mining analysis.
Data and Event Log Quality	The characteristics of the raw data and subsequently constructed event logs.

Phase 2 tackled re-specifying the model using case reports as the empirical base. We performed a hybrid (inductive and deductive) qualitative analysis of 62 process mining case reports written from the user, tool vendor and practitioner perspectives outlining the success stories, tangible benefits and lessons learnt from over 50 organisations. Since process mining cases focus on applying PM tools within a given context, they are noted for providing detailed insights into PM use and outcomes [20]. Qualitatively analysing the insights from these cases provides a detailed understanding of PM success factors from a multi-case perspective. Case reports were sourced from "Process Mining in Action" by Reinkemeyer [3], Task Force for Process Mining (TF-PM) online

case repository[4] and Business Process Management Cases Vol. 1 and 2 [21, 22]. To the best of our knowledge, these sources constituted the most recent collection as of 5th June 2021. While we do not claim this collection to be the only existing source of PM case reports, we do believe them to be representative. An overview of these 62 case reports is provided in Part A of the Supplementary Material (URL in Appendix).

Coding and analysis occurred in multiple rounds. First (Round 1), using an open-coding approach [23], we inductively extracted all direct and indirect content pertaining to elements that contributed to the project's success by analysing each case report text line-by-line. 453 first-level codes were extracted. These were further analysed in a second coding round (Round 2), moving between deductive and inductive (a hybrid approach) coding [24]. The a-priori model from Phase 1 was used as the initial coding classification scheme where relevant open-codes from Round 1 were re-coded under the a-priori CSFs. Those open-codes that did not fit within the a-priori model were inductively grouped to form new themes. The results from here were exposed to another detailed analysis (Round 3). The resulting (sub-) themes from above were critically analysed and refined to obtain conceptual clarity and parsimony of the identified CSFs. This resulted in our final set of CSFs containing nine themes and 23 related sub-themes, outlined in Table 2 and further explained in Section 4.

A coding rulebook was developed to ensure a formalised approach was followed during code extraction [25]. NVivo was used as a qualitative analysis tool to support the coding process. Coder corroborations played a critical role across all rounds of coding. They were essential in forming a unified understanding of identified low-level code groupings, (sub-) themes and descriptions. They also ensured that a credible and high-quality coding process was followed. After the inductive extraction of low-level codes by a primary coder in Round 1, open-codes were discussed and critically reviewed with three secondary coders for alignment to the area of interest (i.e. PM CSFs). The second round of review was conducted after the (sub-) theme extraction phase. Here, coder corroboration aimed to derive consensus on the mapping of lower-level themes to resulting higher-level themes. The third round of corroboration reviewed the forming CSF model as a whole. This focused on ensuring conceptual clarity and parsimony of the nine themes, 23 related sub-themes and their descriptions.

Phase 3 focused on enhancing the re-specified set of PM CSFs. To avoid the critique that CSF studies often provide mere lists of factors without a deeper contextual understanding of how these factors vary in importance over time [13], we identified evidence-based interrelationships between the CSFs and investigated the criticality of these factors, as discussed in Section 5.

We identified potential CSF interrelationships in two ways: (a) by noting and separately capturing any identified interrelationships from the case reports during Round 1 coding as 'Relationship nodes'[5] in NVivo and (b) complementing this method with

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[4] Retrieved from: https://www.tf-pm.org/resources/casestudy. Date: 5th June 2021.

[5] Relationship nodes are special types of nodes that define the connection between two project items.

NVivo's matrix intersection[6] and "near" search queries. Explanations for identified relationships were captured in Memos[7] during the coding process.

Using the case narrative of the identified CSFs, *direct, indirect* and *bilateral* relationships were extracted (see Figure 1 in Section 5.1). The identified interrelationships were further contextualised for PM, applying evidence from the case reports (see Part C of Supplementary Material). A final coder corroboration critically reviewed the evidence supporting each relationship to confirm (a) the existence of each relationship and (b) the nature of the relationship.

4 Re-specified Process Mining Success Factors

While qualitative coding began with the Mans, Reijers, Berends, Bandara and Prince [19] model as a base, our analysis resulted in an extended set of CSF and a re-specified process mining success factors model (see Figure 1). Key differences between our model and prior work (specifically [19]) are outlined in Section 5.

Overall, nine meta-themes (each pertaining to a CSF), with their respective sub-themes, were extracted from our analysis of the 62 reports. These are summarised in Table 2, with a brief description and supporting case-based evidence (i.e., the number of coding references, from how many reports). Example quotes from the case reports are presented in Part B of the Supplementary Material. A detailed explanation of each success factor based on the process mining context, is provided next.

Table 2: Re-specified success factors for process mining

Success Factor	Description	Case evidence summary
a. Stakeholder Support and Involvement	Organisational stakeholders' support or involvement in process mining initiatives.	61 codes from 29 cases
a.1. Management support	Top-Level Management/Senior Executives support.	14 codes from 8 cases
a.2. External stakeholder support	Engagement with external collaborators or industry partners (such as suppliers) who influence an organisation's business process and how they are executed.	5 codes from 5 cases
a.3. Subject matter experts (SMEs)	SMEs of a particular business domain who contribute to process mining efforts.	26 codes from 17 cases
a.4. User groups	The contribution of ultimate users (such as first-line personnel) to process mining outcomes.	6 codes from 5 cases
b. Information Availability	The availability of historical event data and supporting documentation for a process mining initiative.	26 codes from 18 cases
b.1. Event data availability	The extent to which historical event data is available for process mining analysis.	12 codes from 9 cases
b.2. Availability of contextual information	Access to contextual information such as process models, business rules, policy documents, legal and regulatory requirements that can aid process mining.	14 codes from 11 cases

[6] Matrix intersection is a 2-dimensional table that displays coded content from rows and columns.
[7] Memos allow researchers to capture thoughts and reflections during coding to justify coding choices.

c. Technical Expertise	The various forms of technical skills and experience required to execute process mining projects. Four types of technical expertise were identified:	42 codes from 19 cases
c.1. Process mining expertise	The required know-how needed to execute process mining initiatives and interpret outcomes.	6 codes from 5 cases
c.2. Data extraction expertise	The required data analytics expertise for the extraction and integration of event data for process mining.	5 codes from 4 cases
c.3. Process analyst expertise	The required expertise for designing, streamlining, and re-engineering business processes.	2 codes from 2 cases
c.4. Team configuration	The composition of teams and expert groups involved in process mining projects. Two main configurations namely: **Established units:** An internal team dedicated to executing process mining initiatives. E.g., a Centre of Excellence (CoE) (21 codes from 11 cases). **Ad-hoc units:** A group of experts assembled from different departments within the organisation to execute process mining projects as and when required (8 codes from 5 cases).	29 codes from 14 cases
d. Structured Process Mining Approach	The extent to which an organisation follows a structured approach or technique to execute process mining initiatives.	135 codes from 49 cases
d.1. Planning	Identifying questions or project goal(s), selecting business processes to be mined and composing the project team to execute process mining initiatives.	32 codes from 21 cases
d.2. Extraction	Determining the data extraction scope, extracting event data, and transferring process knowledge between business experts and process analysts.	47 codes from 28 cases
d.3. Data processing	Using process mining tools to create views, aggregate events, enrich or filter logs to generate the required insights from event logs.	21 codes from 15 cases
d.4. Mining and Analysis	Applying process mining techniques to answer questions and gain insights.	23 codes from 18 cases
d.5. Evaluation	Relating analysis results to improvement ideas to achieve project goals.	6 codes from 6 cases
d.6. Process improvement and support	Using gained insights to modify the actual process execution.	6 codes from 5 cases
e. Data and Event Log Quality	Provisions made for the extraction, preparation, analysis, and data quality considerations of event data for process mining initiatives.	84 codes from 45 cases
e.1. Data pre-processing	Provisions for the extraction and preparation of event data from single or multiple sources for process mining based on lessons learnt.	61 codes from 40 cases
e.2. Event log quality considerations	The data quality considerations and minimum requirements to be met by event logs for process mining.	23 codes from 17 cases
f. Tool Capabilities	The functionalities and features of process mining tools that organisations can use for process mining.	67 codes from 35 cases
f.1. Process discovery	Automated process model discovery and process visualisation from event data.	27 codes from 20 cases
f.2. Process Benchmarking	Using event data for comparison of process behaviours and process performance.	6 codes from 6 cases
f.3. Conformance checking / Compliance	Detection of deviations from process norms using event data.	16 codes from 15 cases

f.4. Integration capabilities	Integration of process mining capabilities with other data analytics capabilities	7 codes from 5 cases
f.5. Analytical Scalability	The tool's ability to analyse data for insights into single, multiple and e2e processes.	11 codes from 10 cases
g. Change Management	The series of activities that ensure that the needed change emanating from process mining results is implemented in the organisation.	11 codes from 7 cases
h. Project Management	The management of activities and resources, such as time and cost throughout all phases of the process mining project to obtain the defined project outcomes.	9 codes from 8 cases
i. Training	The education and sensitisation of stakeholders on the appropriate execution of process mining initiatives for the intended results.	18 codes from 12 cases

a. Stakeholder Support and Involvement

Deep involvement of key stakeholders early on and throughout a process mining project was an important success factor. Such involvement ensured awareness of stakeholder roles and responsibilities in a process mining initiative. It was also instrumental for "coordinative effort and diverse interaction with respective participants" (Case 8) and addressing challenges encountered during process mining. Four stakeholder groups' involvement were identified. First, **management support –** for some organisations, a top-management driven approach to process mining and the right level of management attention proved strategic in systematising processes within the organisation. Also, establishing roles such as Chief Process Officer could focus more on achieving process excellence goals (e.g., Case 9). Close collaboration with **external stakeholders** such as suppliers and other industry partners could facilitate the transfer of process knowledge from one organisation to the other and influence the ability to execute an e2e process mining approach. Contributions from **subject matter experts (SMEs)** such as process owners, process stakeholders, and managers were instrumental for process mining success. Their expertise provides crucial insights (such as business knowledge, deep contextual understanding of the process being mined, and communicating process changes and guidelines) to other stakeholders, which influences the value of process mining outcomes. Furthermore, **user groups** were instrumental as they provided feedback for verifying process mining results and suggesting process improvements. First-line users were also helpful to "uncover additional factors that influence the process, which are often not visible in the data" (Case 13) and identify the exact trouble spots within a process.

b. Information Availability

The availability of information resources such as event data from business systems, detailed workflows, benchmarking and KPI information, and privacy regulations were considered essential. **Event data availability** for process mining was seen to be of utmost importance. While some organisations had teams to ensure that data was "properly prepared and available in the right place at the right time" (Case 25), the availability of such data in other organisations was a hurdle to overcome because there were "constraints in obtaining "accurate" data since this capability was limited to specialised analytics teams" (Case 2). The **availability of contextual information** such as process models documentation, benchmarking information, and other regulatory and compliance requirements enables a clear understanding of the process and ensures that process mining is appropriately done, understanding contextual factors (e.g., Case 11).

c. Technical Expertise

Technical expertise was crucial for executing process mining projects effectively. Whether such expertise was provided in-house (e.g., CoE) or externally (e.g., consultants), these experts were solely responsible for extracting, preparing, analysing, and interpreting analysis results to provide process insights to relevant stakeholders. Four categories of technical expertise were identified. First, **process mining expertise –**the competence of applying process mining tools was an important skill set. Such expertise was essential for applying analytics techniques to extract data insights. When such skills were lacking, some organisations were forced to limit the use of process mining to specific areas (e.g., Case 11). For **data extraction expertise,** initial data engineering expertise facilitated a successful process mining implementation. To maintain daily use of process mining, some organisations sought to "build data engineering and data science expertise from the early beginning during the implementation. This helped us learn during the project phase and to implement new use cases in short time frames without external support later." (Case 12). Also, data scientists knowledgeable in the data source structure and capable of setting up the required project schema for event data extraction enhanced the quality of process mining insights. **Process analyst expertise -** extensive knowledge in traditional process modelling techniques was critical, as it provided the competence to build new process models in-house (e.g., Case 12). Organisations usually relied on a team-based approach when combining expertise for process mining. A sound **team configuration** was crucial and came in two forms: (i) ***Established units –*** multidisciplinary teams of experts such as business process managers, process analysts and data experts dedicated to undertaking process mining projects. They enable process owners to refine their operations to minimise process variations and implement future process changes. These teams were referred to as; the Centre of Excellence (CoE), Process Excellence Centre (PEC), Process Mining Insights (PMI), Business Process Leadership (BPL) or Process Mining Consulting (PMC) team (e.g., Cases 2, 5 and 12). (ii) ***Ad-hoc units*** are a temporary group of experts assembled from other departments who possess the needed knowledge and expertise to execute process mining initiatives (e.g., Case 31).

d. Structured Process Mining Approach

As the case reports captured diverse approaches to executing PM initiatives, we adopted the PM^2 framework [26] as a unifying and guiding framework to further analyse meta-themes under (**d):** Structured Process Mining Approach.

Most organisations followed some approach or plan for executing process mining projects. A PM project usually begins with **planning** i.e., specifying a goal or an objective, extracting and analysing event data, interpreting insights, and implementing process improvements. Most process mining projects within organisations are motivated either by a process-related goal, problem or an opportunity that needs attention. Planning also involves considerations about executing process mining projects in tandem with organisational objectives (e.g., Cases 7 and 12). A total of 30 cases reported having engaged in some form of planning. **Extraction** involved taking specific actions with regards to identifying data sources and the mode of extraction. 28 cases reported having engaged in some form of data extraction. Steps taken regarding **data processing** indicated that the nature of the process to be mined influenced the form of logs generated for process mining. 15 cases reported activities related to data processing. **Mining and analysis** usually began with the automated discovery of as-is process models to exploring bottlenecks and process inefficiencies. 56 cases reported having engaged in some form of mining and analysis. **Evaluation** focused on comparing analysis results to improvement ideas to achieve project goals. Six cases reported some form of evaluation. **Process improvement and support** were the actions taken to adjust business processes based on newly gained insights. 26 cases reported some form of process improvement and support such as modifying existing KPIs and changing how processes are optimised (e.g., Case 12).

e. Data and Event Log Quality

Organisations acknowledged the significance of data and event log quality as pre-requisites for PM success. Deliberate steps were taken to ensure that event data was of reliable quality. During **data pre-processing,** organisations where data was "structured in a way that closely resembled an event log" minimised "the effort needed to consolidate data" (Case 5). Others with complex data models needed to rely heavily on cross-team collaborations and different technologies to successfully extract event logs for process mining (e.g., Case 5). Organisations also learnt the relationship between data accessibility and valuable insights. Limited data access impaired understanding of the complete flow of activities. For **event log quality considerations**, organisations confirmed high-quality event logs a pre-requisite for obtaining valuable insights into processes. However, there were significant data quality challenges in "pre-processing the data from multiple systems to create high-quality logs" (Case 57). Quality assessment revealed data quality issues such as missing, irrelevant, and misplaced events, granularity and correlation issues, events representing case attributes and diverse activities with the same timestamp (e.g., Cases 3, 15 and 58).

f. Tool Capabilities

Organisations identified key features and capabilities of process mining tools essential for executing process mining projects. Users were keen about the extent to which **integration capabilities** of process mining tools could support existing IT landscapes and other technology such as AI or machine learning techniques (e.g., Case 8). The ability to provide automated **process discovery** and visualisation or process models was a popular feature (in 20 cases), **process benchmarking** (in six cases) and **conformance checking** (in 15 cases) were also highlighted as key capabilities for process mining success. Case 12 also confirmed that "having a realistic view and expectation management of what the tool is capable of" was essential. With **analytical scalability**, organisations were able to analyse a single process or e2e process at various levels of detail and even at high data frequencies (e.g., Case 35).

g. Change Management

Having a well-defined and highly efficient change management approach was critical to accommodate the high rate of continuous change that process mining brings. A change management system was essential for dealing with change across multiple departments, especially in e2e processes (e.g., Case 9). Some organisations (e.g., Case 26) confirmed that the presence of a dedicated individual or team of experts (e.g., a CoE) to lead change management initiatives proved beneficial as they had extensive know-how about digital solutions and organisational processes and could convince end users of the value of process mining.

h. Project Management

Organisations considered the scope, time, and infrastructure resources to support process mining. Organisations that properly managed the implementation of required infrastructural support for PM within reasonable timelines found it essential for its success (e.g., Cases 2, 7 and 10). As the process mining scope widened to an enterprise or global scale, organisations faced further complexities with deployment (e.g., Case 7). It was also discovered that to deploy process mining on a global scale, having a clear governance structure was crucial as it supported the goals, direction, and objectives of the organisation.

i. Training

The case reports indicated that to fully enjoy the benefit of process mining analytical capabilities, end users needed to be trained on how to use the tool. Training occurred either internally (e.g., Case 5) or by external consultants (e.g., Cases 22 and 37). Aside from creating awareness of the usefulness and power of process mining, these educational sessions aimed "to fully engage the true end users and immerse them in the world of Process Mining" (Case 5). They also provided the needed upskilling for technical staff on using PM tools.

5 Discussions

5.1 An Enhanced PM CFS Model

From the re-specified PM success factors in Section 4, we present an enhanced PM CSF model. This differentiates our work from existing PM CSF studies (e.g., [19]) in that, not only do we present a more comprehensive set of CSFs from a broad and contemporary case base, but we also identify inherent relationships between the factors to better understand which CSFs to prioritise. Table 3 describes the types of factor relationships identified from the case evidence in Section 3.

Table 3: Types of factor relationships identified

Type of relationship	Description
Direct relationship	Capture how one factor can influence another (implying a causal relationship between one CSF and another).
Indirect relationship	Relationships whose outcomes are influenced by either moderating or mediating variables. A moderating variable alters the direction or strength of the relationship between a predictor and an outcome, i.e.; it addresses the "when" or "for whom" a variable most strongly predicts or causes an outcome. A mediating variable is the mechanism through which a predictor influences an outcome, i.e., it establishes the "how" or "why" one variable predicts or causes an outcome variable [27].
Bilateral relationship	A two-way relationship between two CSFs, indicating that they can concurrently influence each other reciprocally.

Figure 1 summarises the results, representing a new process mining critical success factors model. Part C of the Supplementary Material provides supporting evidence for each relationship. Overall, 14 relationships were identified, each outlined below.

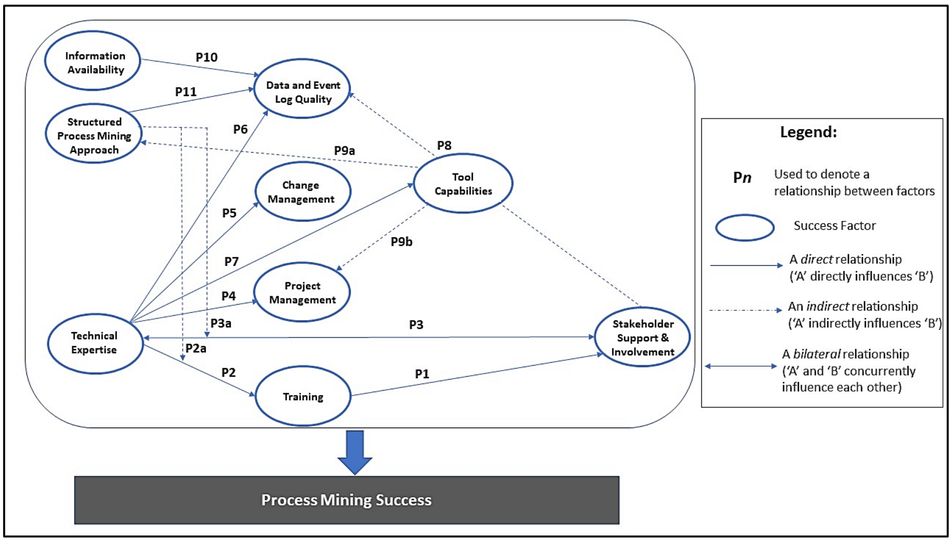

Figure 1: An enhanced PM CFS model with factor relationships based on case data

Multiple cases indicated how **Training** contributes to **Stakeholder support and involvement** [**P1**]. Diverse forms of training such as customised classroom training, on-the-job training, online webcasts for specific topics, and open sessions, were conducted across several cases (e.g., Cases 5, 6 and 12). However, all case observations on **P1** related to the training of end users. If and how training may influence other stakeholder groups such as managers, external parties or SMEs was not evidenced from the data.

Furthermore, the case data depicted how **Technical expertise** contributed to **Training** [**P2**]. Case 2 describes how a small team of data scientists [**Technical Expertise**] ensured that "the end users were trained with the required skills to process mine." These same data scientists also served as "points of contact for other business departments to help them scale out the capability locally" (Case 2). At times (e.g., Case 22), this training was extended to different staff groups (beyond the end users) and embedded with the steps of the **Structured Process Mining Approach** [**P2a**]. Thus, **Structured Process Mining Approach** could moderate the relationship between **Technical expertise** and **Training**.

A bilateral relationship was observed between **Technical expertise** and **Stakeholder support and involvement**, in particular with the SMEs [**P3**], where the cases vividly explained how the SMEs and the technical teams were "working in parallel" (e.g., Case 26) and how at times the SMEs "set the directions of analysis and conduct" for process mining (e.g., Case 28). P3 was facilitated in a moderating manner by the **Structured process mining approach** [**P3a**], where the SMEs were contacted to verify the data and results from process discovery (e.g., Case 50) or while analysing logs together (e.g., Case 41).

Technical expertise enables the overall **Project management** [**P4**] of process mining initiatives. For example, Case 2 attributes its success to the "huge efficiency gains" obtained from a small, well configured technical team. And Case 12 describes how building the technical expertise enhanced the project management efforts and outcomes, particularly helping them "learn during the project phases and to implement new use cases in short time frames without external support later". Similarly, **Technical expertise** enables the overall **Change management** [**P5**] of process mining initiatives. For example, Case 14 describes how business and process analysts' technical expertise, particularly their "know-how of the digital solutions in use" (i.e., the configurations and underlying processes), were integrated into change management plans.

Technical expertise influenced the impact of **Data and event log quality** [**P6**]. Data quality issues could quickly be resolved when **Technical expertise** was high (e.g., Case 10). On the contrary, when the required competency was lacking, data quality issues were very difficult to resolve (e.g., Case 11). Similarly, case studies such as Case 2 illustrate the critical role that **Technical expertise** plays to maximise **Tool capabilities** [**P7**] to "ensure the tool performed as needed".

Tool capabilities influence (in a mediating manner) how the different **stakeholders get involved** and support **Change management** [**P8**]. Case 6 describes how tool features such as "benchmarking inside the same process using different context" are "useful to understand how the process owner could make some process improvements to increase the entire process performance", thus increasing the overall interest and acceptance of process mining. Case 10 explains how the tool's seamless integration into the analytics platform helped the users to accept process mining solutions quickly. **Tool capabilities** also played a mediating role between the **Structured process mining approach** [**P9a**] and the overall **Project management** [**P9b**]. For example, Case 51 describes how **Tool capabilities** such as automatic process discovery allowed the team (i.e., Project Management) to efficiently execute core steps within the planned process mining approach and “identify improvement opportunities, prioritise them, and achieve benefits.”

Information availability can enhance or inhibit **Data and event log quality** [**P10**]. For example, Case 25 articulates the need for the master data to be “properly prepared and available in the right place at the right time” to enable process mining. Case 43 describes the crippling effect that poor IT controls has on accessing essential data for effective process mining. Case 2 elaborates on similar challenges when access to “accurate data” is limited to only specialised teams.

Structured process mining approach influences **Data and event log quality** considerations [**P11**]. It was seen that the data architecture, data extraction techniques and software tools used by the organisation for process mining influenced future considerations for data and event log quality (e.g., Cases 3 and 4). Once these stages were well-outlined, future efforts were easier. Case 13 states: “given that the data preparation steps are now in place and can be easily repeated on new data, we can now continue to analyse and quantify this process to continuously improve it”. Organisations also learnt that 80% of all process mining efforts were focused on data extraction, data preparation and dealing with data quality issues (e.g., Case 15).

Overall, the analysis depicted how some factors are at the core, influencing several other factors. For example, **Technical expertise** influences six other factors, namely **Stakeholder support and involvement, Training, Data and event log quality, Change management, Tool capabilities** and **Project management**. Williams and Ramaprasad [15] describe the value in recognising these direct/indirect relationships, for they assist in determining the order in which the success factors need to be addressed. For example, the findings show that investing in technical expertise will influence many other factors and, hence, be better than investing in other factors such as Project or Change Management efforts.

5.2 Limitations

Our study relies on insights from 62 published case reports to derive our enhanced PM CSF model. Though the 62 cases cover a wide range of PM contexts, we acknowledge that our findings are limited to the information documented in these case reports and are bounded by the scope, bias, and limitations of these reports. Our findings are also exposed to other limitations of secondary data analysis and qualitative research in general, such as possible selection and researcher bias in the case/code selection and overall analysis.

5.3 Contributions

Our theoretical contributions are three-fold. (i) Using state of the art evidence from a wide range of PM success stories, we provide a more comprehensive and in-depth understanding of success factors that extends prior PM CSF research. (ii) We also identify CSF interrelationships and explain which factors have direct, indirect or bilateral influences on attaining process mining success. Finally, (iii) this work provides a sound basis for future research (see Section 5.4).

Our PM CSF model is of practical value. The comprehensive details of PM CSF derived from practice enables PM stakeholders to focus on the essential antecedents for PM success and plan accordingly. The summary analysis presented (e.g., the frequency of case data supporting each factor as outlined in Table 2) indicates the different degrees of importance of the factors. The identified interrelationships enable PM project managers and sponsors to determine which CSFs to prioritise when addressing CSFs. Knowledge about which factors have direct, moderating, mediating or bilateral influences on PM project success will also be key when planning PM CSF investments.

5.4 Future research

Our findings are initial outcomes of an ongoing PhD research. The derived outcomes presented herein are bound by the scope of the analysed case report data. Future work will validate our success factors model using primary data collected from in-depth case studies, specifically to confirm the factor configuration and validate the factor interrelationships. These in-depth studies would also be used to further explore how these factors may vary in importance during PM projects and to identify mechanisms for actualising these CSFs across diverse contexts. Our model could also be extended to integrate success measures and provide deeper insights into a complete nomological net explaining how CSFs create impact in a process mining context. These proposed in-depth case studies can be followed by a quantitative survey (with data from global PM initiatives) to statistically test the success factors and proposed relationships to ascertain their degree of influence on the success of PM initiatives. It is also recommended that, where feasible, an investigation into the extent to which the identified CSFs contributed to failed process mining projects be considered. This would guarantee the presence of these factors as "sufficient conditions" for achieving successful process mining initiatives and provide deeper insights on what constitutes and may influence PM project failure.

6 Conclusion

This study explored critical success factors within the process mining domain. Existing process mining CSF studies (e.g., [19]) do not explore factor interrelationships which is a major criticism in CSF literature [14]. Following a hybrid qualitative analysis approach, our work extends the Mans, Reijers, Berends, Bandara and Prince [19] model by qualitatively analysing evidence from 62 recent case reports from diverse industry settings. Our model presents nine PM Critical Success Factors. In addition to the six CSF from Mans, Reijers, Berends, Bandara and Prince [20], which formed our a-priori model, we identified three new factors: **Change management**, **Tool capabilities** and **Training**. Our analysis confirms that three of the six success factors from Mans, Reijers, Berends, Bandara and Prince [19] still hold true, namely **Structured process mining approach**, **Data and event log quality** and **Project management**. However, we re-specified the scope of the other three: Management support, Resource availability and Process miner expertise, which we now term **Stakeholder support and involvement**, **Information availability** and **Technical expertise**. We presented clear descriptions for each factor, identified sub-factors where necessary and explained how they pertain to the current process mining context. We explore factor interrelationships where we found **nine** direct, **five** indirect (**two** moderating, **three** mediating) and **one** bilateral relationship between the CSFs.

7 Appendix: Supplementary Material

Supplementary material for this article is available online at https://bit.ly/3qrtrOE. It contains three parts: Part A provides an overview of 62 published case reports, Part B provides example quotes that support success factor explanations, and Part C presents case evidence supporting the identified CSF relationships.

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