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Faculty of Business Economics

Master of Management

Master's thesis

Cognitive Biases in the BPM life-cycle: A literature review

Lorna Mendoza

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :
Prof. dr. Mieke JANS

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Abstract

Purpose – The purpose of this study is to explore the presence of cognitive biases in the Business Process Management (BPM) life-cycle and their impact on each phase of it. The study aims to identify the cognitive biases that are most prevalent in each stage of the BPM life-cycle and to provide practical implications for future research.
Design/methodology/approach – The study involves a step-by-step analysis of articles pertaining to each stage of the BPM life-cycle. The research platforms utilized for this study were Scopus and ProQuest. The link between the BPM life-cycle and cognitive biases was made through the challenges, issues or approaches found on the literature review.
Findings – The present study found 42 articles related to the challenges of each stage of the BPM life-cycle, and only 28 were able to link with cognitive biases. Within this study, it was found that certain cognitive biases recurred across multiple stages of the BPM life-cycle. The confirmation trap, for instance, manifested in the process discovery, process analysis, process redesign, and process monitoring phases, while the anchoring bias appeared in the process discovery, process analysis, and process implementation phases. Similarly, overconfidence bias was evident in the process analysis and process redesign stages, and the ease of recall bias manifested in the process discovery and process implementation stages.
Originality/value – By doing the literature review, potential interrelations among the BPM life-cycle and cognitive biases are identified. This study helps in having a better understanding of where potential cognitive biases can occur within the BPM life-cycle. It should be noted that these findings present an initial stepping stone for potential investigations into the human factors that influence the BPM life-cycle.
Keywords BPM, cognitive, bias, lifecycle
Paper type – Literature review

1 Introduction

Globalization, the evolution of the workforce, and digitalization are transforming the global business environment. As the world is constantly changing and adapting, managers must quickly evolve their approach to improving businesses. To do this, they must rely on IT and keep up with mega-trends, as these have profound implications for business models, processes, and organizational structures (Acciarini, Brunetta, & Boccardelli, 2021). Managers should develop and leverage specific qualities to be effective decision-makers and improve business processes. In essence, decision-makers should be able to detect signals and deeply understand trends to adapt their vision, business model, and strategy while striving to achieve business goals (Acciarini et al., 2021). However, managers tend to be biased during that process due to different factors (Das & Teng, 1999).

To improve operational efficiency, managerial teams focus on re-designing a process where decision-making is essential throughout a collection of activities and events. However, it is crucial to recognize that these decisions may be susceptible to the impact of certain decision biases, given that human choices are easily influenced (Acciarini et al., 2021). In particular, cognitive biases are inherent in human thinking on decision-making processes, and they directly influence business outcomes (Das & Teng, 1999). In recent years, there has been increasing interest in understanding cognitive biases and their effects on various business processes such as strategic planning, risk assessment, and organizational decision-making ((Bazerman & Moore, 2012); (Brooks, 2011); (Eberlin & Tatum, 2005); (Morgeson & Campion, 1997)). The studies aim to know which types of biases are the most common in business processes and, therefore, help managers achieve their goals more effectively (Das & Teng, 1999).

This study aims to thoroughly investigate the potential role of specific cognitive biases in influencing the decision-making process within the Business Process Management (BPM) life-cycle. It will review literature about biases, specifically cognitive ones, the BPM life-cycle, and their intertwining. Due to the increasing number of studies focused on BPM, a critical assessment of this existing literature will be provided. Hence it can be identified which cognitive biases occur where precisely on the BPM life-cycle. According to these considerations, this investigation addresses the following research question: *Which cognitive biases are the most common during business process management life-cycle?* Thus, this article aims to propose an integrative theoretical framework to reconcile theories on cognitive biases that will impact business outcomes.

Moreover, the present article examines the plausible correlation between cognitive biases and the BPM life-cycle. Particular emphasis is placed on elucidating the challenges encountered during each stage of the BPM, as evidenced by the findings from the literature review. While these topics are typically treated as distinct entities, the investigation revealed a gap in the literature concerning the intersection of the BPM life-cycle and its susceptibility to cognitive biases that potentially impact each stage.

Section 2 will focus on the background, delving into the classification of cognitive biases, as well as elucidating the cognitive processes that underlie these biases and their impact on decision-making in business processes. Section 3 will delineate the research approach and its design. Subsequently, the results will be presented, offering a summary of the reviewed studies about each specific phase of the BPM life-cycle and making remarks about each study's challenges. Section 5 will intertwine the studies and the potential cognitive biases that might affect each stage of the BPM life-cycle. Section 6 will discuss the implications of the study's findings, strengths and limitations, a summary of the results and overall review, and some recommendations for future research.

2 Background

This section addresses the definition and classification of cognitive biases as studied in the cognitive science and psychology fields. In addition, the BPM life-cycle and an explanation of each stage of this will be provided.

2.1 Cognitive biases

Cognitive bias is a general term that was initially introduced by Tversky and Kahneman (1974); these biases are defined as cognitions or mental behaviors that will prejudice the decision quality in a remarkable number of decisions for a significant number of people (Arnott, 2006). These biases are an inherent aspect of human reasoning and are often called decision or judgment biases. Arnott (2006) also suggests that these cognitive biases could be seen as predictable deviations from rationality. To better understand this, it is essential to define what is meant by a rational choice, which is a choice that will be based on the decision maker's available resources and the potential consequences of their choice (Dawes & Kagan, 1988). Scholars specialized in cognitive psychology have identified several heuristics and biases that humans are subject to during decision-making under uncertainty (Bazerman & Moore, 2012; Connolly, 1982a; Slovic, Fischhoff, & Lichtenstein, 1977; Tversky & Kahneman, 1974). Heuristics can be described as simplifying strategies employed to navigate complex issues and problems (Caputo, 2013). According to Newell, Simon, et al. (1972), heuristics are cognitive shortcuts that the human brain commonly relies upon when faced with time constraints or limited access to data during the decision-making process. While heuristics can lead to accurate or partially accurate judgments, it is inevitable that individuals will adopt some form of heuristic reasoning (Bazerman & Moore, 2012).

In this sense, Bazerman and Moore (2012); Tversky and Kahneman (1974); Baron, Beattie, and Hershey (1988); Kahneman (2003) have identified some heuristics that may lead to cognitive biases, such as availability, representativeness, confirmation, affect heuristic, bounded awareness, and risk aversion.

- The availability heuristic refers to the tendency of individuals to assess the likelihood, frequency, and causes of an event based on the ease with which instances of that event come to mind or are recalled from memory. This mental shortcut relies on the number of occurrences or the ease of recalling instances of a particular situation as a basis for judgment (Tversky & Kahneman, 1974).

- The representativeness heuristic manifests when individuals form judgments about other individuals, objects, or events. In this cognitive process, individuals tend to search for characteristics that align with preexisting stereotypes (Tversky & Kahneman, 1974).

- The confirmation heuristic arises when people use specific data that aligns with their hypotheses (Baron et al., 1988).

- The affect heuristic is based on the premise that judgments are influenced by emotional evaluations that occur prior to any higher-level reasoning processes. (Kahneman, 2003).

- Bounded awareness heuristics manifest when individuals unconsciously and automatically filter information to prevent themselves from becoming overwhelmed by the volume of available information. However, during this filtering process, there is a risk of unintentionally disregarding or neglecting useful, observable, and relevant data (Bazerman & Moore, 2012).

- Risk aversion concerns the phenomenon where individuals treat risks associated with perceived gains compared to risks associated with perceived losses (Kahneman, 2003).

2.1.1 Psychology literature

One of the pioneers to make an extensive lab experiment, Tversky and Kahneman (1974), describe that biases could result from three significant heuristics: representativeness, availability, and adjustment and anchoring. For instance, the bias will be availability-based when the estimates are being distorted by the influence of factors such as concreteness, drama, familiarity, relevance, similarity, or vividness of instances (Billings & Schaalman, 1980). In other words, when imagining what could happen, individuals remember similar past situations (Connolly, 1982a). Adjustment and anchoring heuristic refers to when decision-makers tend to make some judgments that are based on an initial assessment as an anchor. However, they do not make sufficient adjustments later on (Das & Teng, 1999). As previously stated, Tversky and Kahneman (1974) mentions that each heuristic may lead to several cognitive biases. For instance, the concept of availability leads to biases such as retrievability[1] and imaginability[2], among others. Moreover, researchers have highlighted different cognitive biases, including the illusion of control (Langer & Roth, 1975), hindsight (Fischhoff, 2003), and overconfidence (Fischhoff, Slovic, & Lichtenstein, 1977). In their work, Kahneman and Lovallo (1993) refer to the 'inside view,' which characterizes decision-makers' tendency to perceive their problems as unique, enabling them to disregard historical statistics. Connolly (1982b) provides a comprehensive summary of numerous research findings, identifying 29 distinct biases that frequently arise in decision-making processes. Similarly, Bazerman and Moore (2012) explores 12 cognitive biases commonly observed in managerial decision-making based on their own approach to heuristics.

2.1.2 Strategy literature

In the strategy literature, scholars have identified different biases potentially affecting the strategic decision process (Das & Teng, 1999). For instance, Duhaime and Schwenk (1985) compiled a comprehensive inventory of four cognitive biases. Firstly, *reasoning by analogy* posits that analogies and metaphors serve as models for phenomena, directing attention toward specific aspects and variables. Secondly, *the illusion of control* denotes the tendency to evaluate potential acquisition candidates inadequately. Decision-makers may overestimate the degree of personal control they possess over the outcomes of acquisition and erroneously believe they can ensure the success of the business in the face of challenges. Thirdly, *escalating commitment* arises when executives become deeply committed to a particular unit they have acquired, persisting even in the presence of subsequent evidence indicating poor performance below initial expectations. In essence, decision-makers remain dedicated to a chosen alternative despite receiving negative feedback. Lastly, *single outcome calculations* highlight the tendency within organizations for shared beliefs

[1] Suggests that the most trustworthy ideas stem from information that is readily accessible, even if it may not be entirely accurate (Pompian, 2011)

[2] An event may be judged more probable if it can be easily imagined (Arnott, 2006)

to limit the range of considered alternatives. This simplifies the evaluation process by focusing attention on the most promising options (Duhaime & Schwenk, 1985).

2.1.3 Management literature

Given that not all decision processes are the same, authors Das and Teng (1999); March and Shapira (1987); Bazerman and Moore (2012); Zajac and Bazerman (1991) explore the presence of different biases due to the fact that it depends on the situation. For instance, Zajac and Bazerman (1991) analyzed the cognitive biases and the "blind spots" in competitive decision-making. They included non-rational escalation such as commitments, overconfidence in judgments, and limitations in perspective and problem framing (Chao, 2011). Another classification was brought by Das and Teng (1999). They adopt and modify the list of biases that Bazerman and Moore (2012); Connolly (1982b); Schwenk (1985) provide in their studies. Given that, Das and Teng classified cognitive biases into these forms: (1) prior hypotheses and focusing on limited targets; (2) exposure to limited alternatives; (3) insensitivity to outcome probabilities; and (4) illusion of manageability.

To offer a more detailed exploration, Das and Teng (1999), propose the bias of *prior hypotheses and focusing on limited targets*, and mentioned that decision-makers tend to bring previously formed beliefs when making a decision. In addition, managers tend to focus their attention on specific key objectives that they find more interesting, and therefore they usually ignore information about other worthwhile purposes. The subsequent bias is *exposure to limited alternatives.* They explained that decision-makers only expose themselves to a limited number of possibilities to achieve the same goal (March & Shapira, 1987). In decision-making situations, the information usually is incomplete. Therefore, managers tend to focus on a small batch of options (Simon, 1958). As a result, decision-makers tend to use intuition to complement rational analysis (Fredrickson, 1984). The third bias in their research is *insensitivity to outcome probabilites*; different researchers have shown that decision-makers do not comprehend and usually do not estimate the outcome of the probabilities (Kunreuther, 1976; Slovic, 1967). Management teams are generally more influenced by the value of possible outcomes rather than the magnitude of the possibilities (Shapira, 1995). Lastly, *illusion of manageability*, this bias could be led into two ways. The first is that managers may inappropriately perceive a higher success probability than the objective probability would warranty it (Langer, 1975; Langer & Roth, 1975; Lefcourt, 1973); therefore, decision-makers will have the illusion of control, and they will tend to form overly optimistic estimates. In comparison, managers tend to overestimate the extent to which an outcome is under their reach, believing that the risk can be reduced by using their professional skills. The second way this bias manifests is that decision-makers have the illusion that the consequences of those decisions are manageable. They inaccurately assume that whichever problem arises, they can fix them (Shapira, 1995).

Given the extensive literature available on cognitive biases in different domains (Das & Teng, 1999; Bazerman & Moore, 2012; Arnott, 2006; Zajac & Bazerman, 1991), we determined that the most effective approach for synthesizing this information is through the utilization of Table: 1 by providing an overview of the cognitive biases and corresponding heuristics that Bazerman and Moore (2012) identified since their study addresses insights about cognitive biases within the managerial decision-making context.

Table 1: Overview of the cognitive biases and corresponding heuristics

Bias	Description	Emanating heuristics
1.Ease of recall	Individuals judge events more easily recalled from memory based on vividness or recency to be more numerous than events of equal frequent instances, which are less easily recalled.	Availability heuristics
2.Retrievability	The search process is influenced by individuals' memory structures, leading to biased assessments of event frequency.	Availability heuristics
3.Insensitivity to base rates	Even when irrelevant, individuals tend to disregard base rates while assessing event likelihood if other descriptive information is available.	Representativeness heuristics
4.Insensitivity to sample	Individuals often overlook the significance of sample size when evaluating the reliability of sample information.	Representativeness heuristics
5.Misconceptions of chance	Even when the sequence is too short for statistical validity, individuals anticipate that data generated by a random process will exhibit a "random" pattern.	Representativeness heuristics
6.Regression to the mean	Individuals often ignores the tendency of extreme events to revert towards the average on subsequent trials.	Representativeness heuristics
7.The conjunction fallacy	Individuals misjudge that a conjunction (two events occurring) is more probable than a broader set of events in which the conjunction is a subset.	Representativeness heuristics
8.The confirmation trap	Individuals usually search confirmatory information for what they believe is true and fail to seek evidence that might disconfirm it.	Representativeness heuristics
9.Anchoring	Individuals make estimations of values based upon an initial value -derived from past events, random assignments, or information available- they generally fail to make adequate adjustments from that initial anchor when determining a final value.	Confirmation heuristics
10.Conjunctive and disjunctive event bias	Individuals tend to overestimate the probability of conjunctive events and underestimate the probability of disjunctive events	Confirmation heuristics
11.Overconfidence	Individuals usually get overconfident. When faced with moderately to extremely difficult questions.	Confirmation heuristics

(continued)

Table 2: Overview of the cognitive biases and corresponding heuristics, pt. 2

Bias	Description	Emanating heuristics
12. Hindsight and the curse of knowledge	After learning the occurrence of an event, individuals tend to overestimate their ability to have correctly predicted the outcome. Additionally, individuals tend to neglect information that is unique to them when making predictions about the behavior of others.	Confirmation heuristics
13. Information selection	Individuals often disregard significant information while simultaneously focusing on equally accessible but irrelevant information.	Bounded awareness
14. Inattentional blindness	Individuals fail to notice unexpected events in their visual field, even when they are fully visible, due to their attention being focused on something else.	Bounded awareness
15. Change blindness	Individuals tend not to notice a visual change in their physical environments.	Bounded awareness
16. Focalism	Individuals often allocate excessive attention to a specific event while neglecting other events that are equally probable.	Bounded awareness
17. Framing	Individuals' reactions and perceptions can vary based on the framing of a problem. The manner in which a problem is presented significantly influences the decisions people tend to make, despite the fact that variations in framing should theoretically have no impact on rational decision-making.	Risk aversion
18.Status quo	Individuals are often inclined to maintain the status quo rather than actively pursuing improvements in their outcomes.	Risk aversion
19.Emotion and cognition collision	The emotional state of an individual during decision-making often yields different outcomes compared to decisions made through deliberate and thoughtful reasoning.	Affect heuristics
20.Self-serving	Individuals will make different decisions even when identical information depends on their role in the situation.	Affect heuristics

2.2 BPM

Business processes are a crucial aspect of managerial activities, and various scholars have provided their definitions. Dumas, La Rosa, Mendling, and Reijers (2018) define it as a collection of inter-related events, activities, and decision points that involve several actors and objects, collectively lead to an outcome of value to at least one customer. Davenport (1994) characterize a process as a sequential arrangement of work activities occurring over a specific period and space with identifiable inputs and outputs. M. M. Glykas (2011) define it as a horizontal linkage of activities necessary to achieve desired organizational outcomes. Lastly, the Association of Business Process Management Professionals, (CBOK, 2009) describe it as an "end-to-end" task that goes further than functional limits, transposing the organization's hierarchical structure to generate some value for the customer.

According to Dumas et al. (2018), Business Process Management (BPM) refers to a body of methods, techniques, and tools to identify, discover, analyze, redesign, execute, and monitor business processes to optimize performance. In addition, BPM implies a constant and permanent organizational commitment to handle the organization's processes (CBOK, 2009). This commitment gives rise to a life-cycle model comprising well-defined stages and feedback mechanisms. This model is used as a managerial practice for the organization, ensuring it constantly improves, and the processes align with its strategic goals (Macedo de Morais, Kazan, Inês Dallavalle de Pádua, & Lucirton Costa, 2014). Although there are different types of BPM life-cycles, the majority can be described as a sequential series of activities that involve iteration and different phases. These activities typically include (1) Process identification; (2) Process discovery; (3) Process analysis; (4) Process redesign; (5) Process implementation; and (6) Process monitoring (Dumas et al., 2018). Figure:1 illustrates the proposed BPM life-cycle model of Dumas et al. (2018), consisting of the six steps previously mentioned.

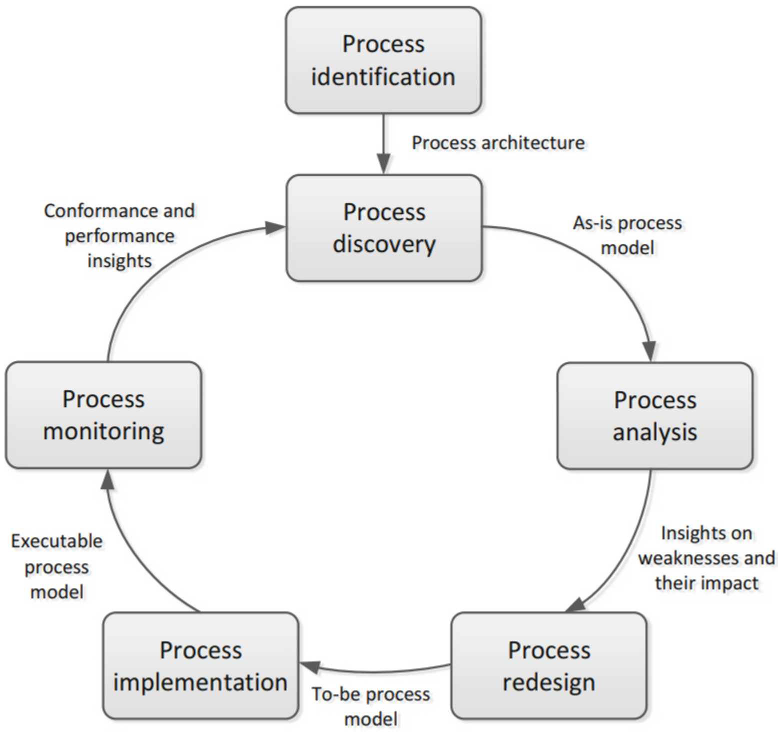

Figure 1: Life-cycle proposed by Dumas et al., (2018, p.51)

2.2.1 BPM Life-cycle

This section aims to present an overview of each phase of the BPM life-cycle proposed by Dumas et al. (2018), enhancing our comprehension of the activities taking place at each stage of the cycle.

The life-cycle starts with *Process identification*. During this phase, the initial step involves presenting a business problem. Subsequently, the pertinent processes related to the addressed problem are identified, defined, and interconnected. The outcome of this process identification stage yields a revised or novel process architecture, which provides a comprehensive overview of the organization's processes and their interdependencies. This architecture serves as the basis for selecting which process or group of processes to manage throughout the subsequent phases of the life-cycle. Typically, the process identification phase runs concurrently with the identification of performance measures.

Process discovery, also known as "as-is"[3] The modeling of the process is carried out in this phase. Here, the existing state of each relevant process is documented, often through one or more as-is process models.

Process analysis, entails the identification and documentation of issues associated with the as-is process, along with the attempt to quantify them using performance measures whenever feasible. The output of this phase comprises a well-structured compilation of issues, which are then prioritized based on their potential impact and the estimated effort required for resolution.

The goal of the *Process redesign* phase, also referred to as process improvement, is to identify alterations to the process that would effectively address the issues identified in the previous phase and enable the organization to achieve its performance objectives. Various change options are analyzed and compared using the selected performance measures. Thus, process redesign and process analysis work in tandem: as new change options are proposed, they are assessed using process analysis techniques. Eventually, the most promising change options are retained and consolidated into a redesigned process. The typical output of this phase is a to-be [4] process model.

Process implementation, involves preparing and executing the necessary changes to transition from the as-is process to the to-be process. Process implementation encompasses two aspects: organizational change management and automation. Organizational change management refers to the activities required to modify the work practices of all participants involved in the process. Process automation, the primary focus of this discussion, pertains to developing and deploying IT systems, or improved versions of existing systems, that support the to-be process.

Once the redesigned process is operational, the *Process Monitoring* phase commences. This phase involves collecting and analyzing relevant data to assess the process's performance in relation to its performance measures and objectives. Bottlenecks, recurring errors, or deviations from the intended behavior are identified, prompting the implementation of corrective actions. This continuous monitoring process may uncover new issues, either within the same process or in others, necessitating the repetition of the cycle.

[3]The as-is process models show the understanding that people within the organization have about how work is done. Process models have the purpose of easing communication between stakeholders involved in a BPM initiative (Dumas et al., 2018).

[4]A redesign version of the process based on the understanding of the issues and challenges found on the process (Dumas et al., 2018)

3 Methodology

In order to find which cognitive biases might be affecting each of the phases of the BPM life-cycle, it was conducted a literature review (Cook, Mulrow, & Haynes, 1997; Cooper, 1998; Denyer, Tranfield, Buchanan, & Bryman, 2009; Tranfield, Denyer, & Smart, 2003). This research method was brought up in the UK medical profession of the need for better evidence-based research. Since then, it has been used throughout many disciplines, including management research (Thorpe, Holt, Macpherson, & Pittaway, 2005). The primary goal of this method is to gather and connect a wide range of relevant studies on a specific research topic.

In this study, the chosen methodology involves a step-by-step analysis of articles pertaining to each stage of the BPM life-cycle. The research platforms utilized for this study were Scopus and ProQuest; due to Scopus comprises more than 20,000 peer-reviewed journals (Mishra, Gunasekaran, Papadopoulos, & Hazen, 2017), we relied heavily on that database. To pinpoint articles relevant to specific life-cycle stages (process discovery, analysis, redesign, implementation, and monitoring), we fine-tuned search terms accordingly, incorporating the "lifecycle" keyword as well. The search strategy varied between the two databases. For ProQuest, it was stipulated that search terms must appear in either the abstract or summary of articles to ensure focus on life-cycle-related studies. Conversely, for Scopus, inclusion criteria encompassed the presence of search terms in titles, abstracts, or document keywords. This methodology facilitated the identification of pertinent articles addressing life-cycle stages and objectives.

As indicated in Table 3, a comprehensive overview of the search results across each database platform is presented, elucidating the executed search strategy. The review comprises English peer-reviewed journal articles only. To narrow the search, we had to restrict the search criteria; in the ProQuest database, the search domain was confined to "business process management," while in Scopus, the scope was refined to encompass articles within the field of "business, management, and accounting" only.

Subsequently, articles corresponding to each life-cycle phase were combined into a unified database, with the exception of the initial phase, process identification, as it primarily addresses the presentation of the business problem (Dumas et al., 2018). This integration facilitated an initial assessment for duplicate entries. Following this, an evaluation of the article's relevance took place. Relevance was evaluated based on alignment with the purpose of this research. The articles that were chosen had to specifically address challenges, issues, or improvements relevant to the specific life-cycle phase under examination. After analysis, the overall count of articles decreased further, as highlighted by the data in Table 3.

Notably, the articles chosen for this review exclusively focus on challenges, issues, or improvements within each stage of the BPM life-cycle. However, none of these explicitly address cognitive biases. To bridge this gap, we embarked on an effort to interweave cognitive biases with the BPM life-cycle phases. This effort involved an analysis of each challenge, issue, or improvement reported in the articles unearthed through our research.

Stage	ProQuest	ProQuest search terms	Scopus	Scopus search terms	Total
Process Discovery	n=4	summary(process discovery) AND summary(lifecycle)	n=7	process AND discovery, AND lifecycle	n=9
Process Analysis	n=14	summary(process analysis) AND summary(lifecycle)	n=10	process AND analysis, AND lifecycle	n=11
Process Redesign	n=16	summary(process redesign) AND summary(lifecycle)	n=9	process AND redesign, AND lifecycle	n=9
Process Implementation	n=9	summary(process implementation) AND summary(lifecycle)	n=7	process AND implementation, AND lifecycle	n=12
Process Monitoring	n=5	summary(process monitoring) AND summary(lifecycle)	n=28	process AND monitoring, AND lifecycle	n=6

Table 3: Overview of the search results across each database platform.

4 Results

Starting with an analysis of existing studies, we constructed a framework that emphasizes the prevalent issues, challenges, and approaches documented in the literature review. The following section elaborates on the specific findings from the authors' studies within each phase of the life-cycle. This section is the initial phase in order to establish the connection between BPM and cognitive biases.

4.1 Process Discovery

According to Dymora, Koryl, and Mazurek (2019), process discovery represents a growing and interesting scientific field that focuses on advancing theories and techniques for gathering and representing knowledge about real process execution and the underlying rules guiding organizational activities. Over the past two decades, this area of research has yielded fruitful results in the literature. dos Santos Garcia et al. (2019) conducted a systematic survey, revealing that process discovery's most active research subjects pertain to process mining algorithm development and optimization, conformance checking techniques, and software architecture enhancement. Process discovery is recognized as the foundational mission of process mining (Liu, Cheng, Zeng, & Wen, 2022).

Kouhestani and Nik-Bakht (2020) propose an Industry Foundation Classes (IFC) based process mining solution to analyze and discover end-to-end design authoring processes in the Architecture, Engineering, Construction, and Operation (AECO) industries. During the process discovery stage analysis, the authors encountered challenges related to process mining in the AECO industry, specifically, the lack of standardization and interoperability of data formats and software systems used by different stakeholders. This resulted in difficulties consolidating data from diverse sources and developing process mining algorithms capable of working with varying data formats. The article emphasizes the risk of overfitting concerning process mining algorithms. Overfitting occurs when a model is excessively complex and closely fits the training data, leading to poor generalization performance on new data. In the context of process discovery, overfitting arises when the discovered process model is too specific to the training data and fails to generalize effectively to new data. This can result in incorrect or misleading insights into the actual process behavior and performance. As a solution, the authors propose a two-step approach to balance between overfitting and underfitting, as suggested by van der Aalst, Rubin, van Dongen, Kindler, and Günther (2006). This approach involves initially discovering a general process model and then refining it based on the specific characteristics of the training data.

Moreover, the suggested solution aids in detecting design events and enables in-depth analysis of discovered processes, providing Building Information Modelling managers with support for more effective analysis and decision-making techniques. The authors argue that this portrayed solution can enhance stakeholders' ability to monitor and optimize the business processes within their companies, identifying bottlenecks or activities that may take longer than expected. The article emphasizes the significance of discovering the "as-is" processes, which reflect the actual processes occurring during project execution, instead of solely focusing on the "as-planned" processes. Sobhan highlights the importance of involving domain experts in developing process mining algorithms to ensure their relevance and proper implementation. Collaborating with domain experts ensures that the algorithms align with the specific needs of the AECO industry.

Liu et al. (2022) highlights that several existing process discovery techniques are restricted to generating flat process models from business event logs, thereby being unable to capture the hierarchical structure of business processes. This limitation becomes significant since many business processes within companies exhibit a hierarchical structure featuring subprocesses invoked by other processes. To address this issue, Liu et al. (2022) proposed an approach to discover hierarchical process models using hierarchical Petri Nets (HPNs). These nets represent a type of Petri Nets capable of supporting formal modeling and correctness verification of processes with subprocesses. The article presents a solution to the challenge of discovering hierarchical business processes, which is essential to enhancing the efficiency and effectiveness of information systems that support business processes.

Mahendrawathi, Hanggara, and Astuti (2018) in their article investigate the factors influencing the successful implementation of business process management, specifically focusing on the process discovery phase within the BPM life-cycle. The study presents a case analysis of three companies that underwent enterprise resource planning (ERP) system implementations. The authors examined their approaches to process discovery. They identified several issues that could arise during this phase, including the need for dedicated teams and suitable tools for modeling business processes. These challenges can lead to insufficient focus and resource allocation for process discovery, resulting in incomplete or inaccurate process models. The findings indicate that the three companies either did not prioritize process discovery or needed more adequate resources, such as dedicated teams and appropriate tools. Additionally, it is possible that these companies undervalued the significance of investing in process discovery or needed to comprehend the importance and benefits of BPM implementation fully.

4.2 Process Analysis

The process analysis phase typically constitutes the second step of the BPM life-cycle (Macedo de Morais et al., 2014). This stage involves assessing the current state of the process to identify its strengths, weaknesses, and potential areas for improvement. In one article, the author proposes a framework that underscores the significance of aligning business strategy and processes within BPM activities, a crucial aspect of the process analysis phase.

Another study by Szelkagowski (2021) delves into the relationship between BPM and knowledge management (KM) and explores the types of knowledge utilized in the process analysis. The author argues that organizations should analyze the nature of their business processes in terms of execution and management to tailor knowledge management methods accordingly throughout the execution, analysis, and diagnosis stages. The article also emphasizes the importance of adjusting elements of the BPM ecosystem, specifically during the execution, analysis, and diagnosis stages of the BPM life-cycle, underscoring the significance of process analysis in accurately and effectively managing business processes.

Van der Aalst (2023) introduces the concept of Object Centric Process Mining (OCPM), a holistic and comprehensive approach to process analysis and improvement stages. Unlike traditional approaches that often focus on a single object type, OCPM acknowledges the involvement of multiple object types in various events. Van der Aalst highlights the benefits of this approach and its potential to enhance the process analysis stage within the BPM life-cycle. Additionally, Goldstein, Johanndeiter, and Frank (2019) propose a runtime model that bridges the gap between the design, enactment, and evaluation of business processes. The authors emphasize the need for further research to achieve a comprehensive BPM environment, exploring the potential for dynamic adaptation of workflows and process mining techniques to improve process execution analysis.

Özdağoğlu, Özdağoğlu, and Damar (2023) provide a detailed approach to the process analysis stage of the BPM life-cycle. The article emphasizes the importance of process identification within the life-cycle and the need to establish a manageable scope to ensure effective BPM. Özdağoğlu et al. (2023) recommend using frameworks for process classification to evaluate the list of processes and developing criteria and scales for assessing them. The article also stresses the significance of prioritizing the use of Multi-Criteria Decision-Making methods to observe incompatibilities between evaluation methods. Overall, it presents a comprehensive approach to process analysis aimed at aiding SMEs with limited BPM experience. In the context of IT security risk management, Goldstein and Frank (2016) acknowledge the significance of process analysis. They emphasize that more than providing modeling concepts alone is required to offer appropriate support and that process models are essential for guiding the use of modeling concepts to address a range of IT security issues.

4.3 Process Redesign

These articles delve into various aspects related to process improvement and reengineering, exploring different methodologies, frameworks, and challenges encountered during the process redesign phase. By synthesizing the insights from these academic sources, this compilation aims to provide a comprehensive understanding of the key considerations and approaches in optimizing business processes through effective process redesign.

Vera and Zapata (2022), offer valuable insights into best practices for business process improvement (BPI) and process redesign. The article discusses various academic sources that present different methods and frameworks for BPI and process redesign, such as the Quintessence kernel and successful redesign heuristics. Notably, a study in the article highlights the most successful heuristics, which focus on customer needs, process efficiency, and organizational culture Reijers and Mansar (2005). Vera's work provides a robust framework to assist organizations in enhancing their business processes during the process redesign phase.

Afflerbach, Hohendorf, and Manderscheid (2017) address the challenges of process redesign and proposes a value-based application of evolutionary algorithms (EAs). These challenges include subjective vagueness, lack of guidance and support, and the need for alignment with strategic and operational goals. The adoption of a value-based approach could facilitate objective prioritization of process design objectives. M. Glykas and Valiris (1999) also explore challenges in the process redesign phase, such as confusion regarding terms like re-engineering, process improvements, and redesign. Other challenges involve resistance to methodologies, the misconception that change management should be the central focus of business process reengineering, customer satisfaction, and the requirement for proper control and continuous improvement of the redesign process. Additionally, introducing new technology may impact personnel behavior and attitudes. To address these challenges, M. Glykas and Valiris (1999) emphasize the necessity of effective Business Process reengineering methodologies to foster continuous improvement.

Cho, Song, Comuzzi, and Yoo (2017) propose an evidence-based approach to evaluate the effectiveness of best practices during the process redesign phase. The article introduces a framework incorporating process mining techniques to enhance business processes. It underscores the importance of evidence-based decision-making in business operations. Lastly, Özdağoğlu et al. (2023) discuss the significance of the process redesign phase in relation to process selection. This process selection occurs during the redesign stage of the BPM life-cycle and is regarded as a multi-criteria decision-making (MCDM) problem. The article gathers studies proposing various process selection and prioritization methods, including the Analytic Hierarchy Process (AHP), Balanced Scorecard (BSC), and Fuzzy-AHP. These methods aid decision-makers in prioritizing and selecting alternatives based on criteria, aligning business with their vision and strategy, and accommodating uncertainty and inaccuracy in decision-making. Overall, the article offers an integrated approach to process redesign and selection within the context of BPM.

4.4 Process Implementation

Macedo de Morais et al. (2014) provide a comprehensive description of the process implementation phase as a multifaceted step encompassing various activities, including training, metric policies, performance evaluation, strategic alignment evaluation, risk analysis, and monitoring. The primary focus of this phase is to ensure the efficient and effective execution of designed processes. Process implementation entails the physical design of the process, IT infrastructure, and resource allocation to ensure the achievement of process objectives.

Addressing challenges related to this stage of the BPM life-cycle, Mahendrawathi et al. (2018) highlight two critical aspects in their study of companies in Indonesia. Firstly, organizational change involves restructuring activities to alter the work practices of all involved individuals. Secondly, process automation entails developing and applying IT systems that support the to-be process. Additionally, Macedo de Morais et al. (2014) emphasize the complexity of human involvement in the BPM life-cycle, involving judgments and abilities that cannot be fully automated. This complexity may need to be improved in designing and implementing efficient and effective processes. The article also stresses the importance of aligning business strategies and processes, which can be challenging without effective communication and coordination among process participants. Furthermore, the paper underscores that process implementation requires a sustained commitment to managing organizational processes effectively but achieving this can be hindered by resistance to change.

Neves and Araujo (2023) highlight the significance of considering potential risks and challenges associated with process implementation and suggests steps, such as reviewing controls by architects or developers, to mitigate them. On the other hand, Mahendrawathi et al. (2018) emphasizes the crucial role of change management during the implementation process. The article underscores the relevance of monitoring and controlling during this phase, involving the gathering and analyzing of critical information to assess how well the process performs in alignment with performance measures and objectives.

Acknowledging the practical challenges, Mahendrawathi et al. recognizes that creating a BPM implementation process that fits every organization and circumstance remains complex.

4.5 Process Monitoring

In this stage of the BPM life-cycle, the organization gathers crucial data and analyzes it to assess the performance of ongoing processes, considering performance measurements and objectives. Mahendrawathi et al. (2018) suggests that process monitoring may involve various methods, such as process mining, to identify bottlenecks, recurrent errors, or deviations from expected behaviors, thereby enabling corrective actions to be taken. The study emphasizes the possibility of encountering new issues related to the same processes during this phase, needing continuous iteration of the cycle. Other studies (García-García, García-Borgoñón, Escalona, & Mejías, 2018; Kouhestani & Nik-Bakht, 2020) propose different approaches to address these challenges.

García-García et al. introduce a model-based solution called PLM4BS, incorporating a process modeling metamodel with concepts like metrics and indicators to enhance the accuracy of process measurement. On the other hand, Kouhestani and Nik-Bakht discusses the integration of process mining with Building Information Monitoring (BIM) to control ongoing projects by documenting a detailed history of previous works and utilizing lessons learned in planning future projects. One of the challenges addressed in Kouhestani's study involves systematically capturing the digital footprints of project actors and their interactions with BIM models.

Goldstein et al. (2019) also emphasizes the importance of monitoring the execution of business processes. The article identifies two main challenges in this stage. Firstly, including runtime abstractions in the modeling language to support managers' need to know the specifications of process instances and sets of process instances. Secondly, synchronizing the model and running system while changes occur on both sides ensures alignment even as modifications are made.

These articles offer diverse approaches to address challenges during the final phase of the BPM life-cycle, emphasizing the significance of continuous process monitoring and improvement.

5 Discussion

In the preceding sections, we have examined the challenges, issues, or new approaches associated with each stage of the BPM life-cycle. This section aims to explore the intertwining between the cognitive biases and each stage of the life-cycle, providing a comprehensive understanding of the biases that might impact decision-making and actions at different stages of the BPM life-cycle. By establishing these links, we can identify and address the potential cognitive biases relevant to each stage, facilitating more informed decision-making and improved process outcomes. The cognitive biases that will be used are the ones in section 2 suggested by Bazerman and Moore (2012).

BPM life-cycle phase	Type of cognitive bias	References
Process Discovery	The confirmation trap	Kouhestani and Nik-Bakht (2020); Liu et al. (2022); Mahendrawathi et al. (2018); Dymora et al. (2019); Munir, Kiviniemi, Jones, and Finnegan (2020)
	Ease of Recall	Kouhestani and Nik-Bakht (2020); Mahendrawathi et al. (2018)
	Anchoring bias	Dymora et al. (2019); Munir et al. (2020)
Process Analysis	The Confirmation trap	Szelkagowski (2021); Özdağoğlu et al. (2023)
	Anchoring bias	Szelkagowski (2021); Özdağoğlu et al. (2023)
	Overconfidence bias	Amalfitano, De Simone, Scala, and Fasolino (2020)
Process Redesign	Status quo bias	Maassen (2018); Afflerbach et al. (2017)
	The confirmation trap	Afflerbach et al. (2017); Mustansir, Shahzad, and Malik (2022); M. Glykas and Valiris (1999); Özdağoğlu et al. (2023)
	Overconfidence bias	Afflerbach et al. (2017); Özdağoğlu et al. (2023)
	Focalism	Afflerbach et al. (2017)
Process Implementation	The confirmation trap	Jose, Cappelli, Santoro, and Azevedo (2020); Hayat and Winkler (2022); Cabanillas, Resinas, and Ruiz-Cortés (2020); Neves and Araujo (2023); Macedo de Morais et al. (2014)
	Anchoring bias	Jose et al. (2020); Neves and Araujo (2023); Macedo de Morais et al. (2014)
	Ease of recall	Cabanillas et al. (2020); Neves and Araujo (2023); Mahendrawathi et al. (2018)
	Hindsight and the curse of knowledge	Neves and Araujo (2023)
Process Monitoring	The confirmation trap	Mahendrawathi et al. (2018); Kouhestani and Nik-Bakht (2020)

Table 4: Overview of the potential cognitive biases with the BPM life-cycle literature.

The Table: 4 presents the visual linkage of potential biases that might be affecting the BPM life-cycle phases and the BPM life-cycle itself with the corresponding references that were found in the previous section.

5.1 Process Discovery

The Confirmation Trap
The confirmation trap bias, as identified by Dymora et al. (2019), may lead researchers to selectively seek evidence that supports their existing beliefs while disregarding contradictory evidence, resulting in inaccurate or erroneous conclusions during the process discovery phase. For instance, in the study conducted by Munir et al. (2020), asset owners might become fixated on BIM strategies that align with their pre-existing beliefs, potentially overlooking alternative, more effective approaches. Similarly, in Kouhestani and Nik-Bakht's research, the confirmation trap could influence the interpretation of process mining results, leading to the creation of process models that inaccurately represent the true nature of the process. To mitigate this bias, Liu et al. (2022) propose utilizing Hierarchical Petri Nets (HPNs), which offer a more comprehensive and precise representation of the process, thus reducing the impact of the confirmation trap. Additionally, Mahendrawathi et al. (2018) highlight a challenge in this phase of the life-cycle, wherein the lack of a dedicated team to conduct process discovery might be influenced by the confirmation trap bias. Companies may erroneously believe that their current methods are sufficient and, as a result, may not invest in a dedicated team to focus on this crucial stage.

Ease of Recall
Kouhestani and Nik-Bakht (2020) suggest that involving domain experts in the development and interpretation of process mining algorithms and results can help mitigate some challenges that might be related to the ease of recall bias. These experts can provide valuable insights and domain-specific knowledge to identify and correct this cognitive bias effectively. Furthermore, Mahendrawathi et al. (2018) note that a challenge during this stage of the life-cycle is the lack of specific tools for modeling business processes, which might be influenced by the ease of recall bias. Organizations may underestimate the relevance of process discovery if they have not previously encountered major issues related to incomplete or inaccurate process models.

Anchoring
Anchoring bias can also impact the process discovery phase, as decision-makers might be unduly influenced by the first piece of information they encounter (Dymora et al., 2019). In Munir et al. (2020) cross-case analysis, this bias might cause managers to remain steadfast in a particular BIM strategy, even if it fails to yield the desired results. To mitigate the impact of anchoring bias during process discovery, Liu et al. (2022) propose employing formal modeling and correctness verification techniques, which can aid managers in making more objective and informed decisions.

5.2 Process Analysis

The Confirmation Trap
In the study conducted by Szelkagowski (2021), the confirmation trap bias may

cause organizations to prioritize information that aligns with their existing beliefs during the process analysis phase. To mitigate the effects of this cognitive bias, Özdağoğlu et al. (2023) advocate the use of Multi-Criteria Decision-Making (MCDM) methods, which offer a structured and systematic approach to process analysis and decision-making. Similarly, Amalfitano et al. (2020) propose an approach that involves employing an Application Life-cycle Management (ALM)-based tool to support questionnaire-based gap analysis. The utilization of such a tool could reduce the influence of the confirmation trap by providing a centralized and easily accessible source of information that includes both confirming and contradictory data points.

Anchoring Bias

The anchoring bias may cause organizations to overly rely on initial information during process analysis. In the study conducted by Goldstein and Frank (2016), this bias can lead to the selection of a process model based solely on initial impressions, potentially overlooking other viable options.

Overconfidence Bias

The overconfidence bias may lead managers to believe that a particular process model is more effective than it actually is, based on their personal preferences (Amalfitano et al., 2020). This bias, as identified by Goldstein et al. (2019), can have significant implications during the process analysis phase, potentially resulting in biased decision-making and inaccurate process models.

5.3 Process Redesign

Status Quo Bias

During process redesign, decision-makers may exhibit a status quo bias, wherein they resist changes that could disrupt existing processes and structures. This reluctance to embrace change can hinder the implementation of sustainable practices and the redesign of business models Maassen (2018). Overcoming this bias is crucial for organizations to adapt and evolve effectively in dynamic environments.

The Confirmation Trap

Afflerbach et al. (2017) propose a value-based approach to reduce the impact of the confirmation trap during process redesign. By providing an objective prioritization of process designs based on their value contributions, decision-makers can mitigate the effects of this cognitive bias. Similarly, M. Glykas and Valiris (1999) emphasizes the significance of avoiding mistakes and addressing fundamental questions through the use of modeling techniques and benchmarking. Özdağoğlu et al. (2023) address the problem of process selection and prioritization in BPM, offering approaches to lessen the influence of the confirmation trap during this critical decision-making process.

Overconfidence Bias

To address the overconfidence bias during process redesign, Özdağoğlu et al. (2023) stress the importance of employing structured decision-making methods, such as Multi-Criteria Decision-Making (MCDM) and Balanced Scorecard (BSC), to achieve more objective and informed decision outcomes.

Focalism

Afflerbach et al. (2017) propose a value-based application of evolutionary algorithms to overcome the inherent subjective vagueness associated with focalism bias during process redesign. The article also highlights that cognitive biases may lead to a narrow focus on certain aspects of the process, potentially neglecting other crucial factors that may significantly impact the success of the redesign efforts. By addressing focalism, decision-makers can adopt a more comprehensive and well-rounded approach to process redesign.

5.4 Process Implementation

The Confirmation Trap
Jose et al. (2020); Macedo de Morais et al. (2014), emphasize that a lack of knowledge about the characteristics of a service can significantly impact the process implementation phase. Decision-makers who are more aware of the relevant concepts have a higher likelihood of achieving their implementation goals. However, the confirmation trap bias may alter the decision-making process by causing managers to favor information that confirms their pre-existing beliefs, potentially overlooking alternative approaches. For instance, Hayat and Winkler (2022) highlight how this bias can influence the implementation of blockchain-based platforms for Product Life-cycle Management (PLM), leading managers to prefer a particular platform without fully considering other viable options. Additionally, Cabanillas et al. (2020)mention assumptions made in compliance checking that can limit managers' ability to consider different types of rules and interpretations.

Anchoring Bias
Jose et al. (2020); Neves and Araujo (2023); Macedo de Morais et al. (2014) discuss how the process implementation phase can be influenced by arbitrary definitions of goals derived from the discovery process. This anchoring bias may cause decision-makers to fixate on initial information or goals, potentially neglecting more appropriate alternatives.

Ease of Recall
Cabanillas et al. (2020) point out that some compliance-checking frameworks only address specific requirements, limiting their applicability in certain scenarios during process implementation. Similarly, Neves and Araujo (2023); Mahendrawathi et al. (2018) suggest that the ease of recall bias may lead decision-makers to prioritize processes that are easier to implement or familiar, even if they are not the most effective ones.

Hindsight and the Curse of Knowledge
Neves and Araujo (2023) emphasize the importance of reviewing test controls by architects or developers during process implementation. This practice helps managers avoid falling victim to hindsight bias, wherein they might wrongly believe they could have predicted the success or failure of the implementation retrospectively. By acknowledging the curse of knowledge, decision-makers can take a more objective and forward-looking approach to the implementation process.

5.5 Process Monitoring

The Confirmation Trap
During process monitoring, organizational factors such as leadership, culture, and communication methods may significantly influence the decision-making process (Mahendrawathi et al., 2018). These factors are susceptible to confirmation trap

bias, where decision-makers focus on information that confirms their pre-existing beliefs, potentially overlooking critical insights and alternative perspectives. Additionally, Kouhestani and Nik-Bakht (2020) highlight the high level of variability in task specifications during process monitoring, which can also make decision-makers vulnerable to this type of cognitive bias. The confirmation trap may lead managers to favor information that aligns with their preconceived notions, potentially hindering their ability to objectively assess the monitored processes' performance.

In order to provide a final overview of the literature mentioned earlier and the studies deemed significant for contributing to the identification of potential cognitive biases related to the challenges presented in each phase of the BPM life-cycle, we present Table: 5. This table will offer a comprehensive visual overview of the cognitive biases that were implicitly identified in the articles. Drawing from the findings of the conducted literature review, diverse challenges were revealed by various authors. In light of these insights, we have aggregated the issues and formulated an overarching "overall" issue for each phase of the BPM life-cycle. This approach offers a final perspective, solidifying the connection between the challenges identified in each phase of the BPM life-cycle and the potential influence of cognitive biases on these specific phases.

BPM life-cycle phase	Influencing cognitive bias	BPM issue
Process Discovery	*Confirmation trap, ease of recall, anchoring bias.*	Inaccurate process models
Process Analysis	*Confirmation trap, Anchoring bias, Overconfidence.*	Drawn to conclusions
Process Redesign and Process Implementation	*Status quo, confirmation trap, overconfidence bias, focalism, anchoring bias, ease of recall hindsight and the curse of knowledge.*	Pre-existing knowledge
Process Monitoring	*Confirmation trap.*	Influence of organizational factors

Table 5: Overview of BPM issues and cognitive biases

Inaccurate process models

This phenomenon occurs when organizations undervalue the significance of a particular process, such as process discovery, especially if they have not previously encountered substantial challenges associated with incomplete or inaccurate process models (ease of recall). In certain instances, companies may lack a dedicated team for this specific phase, often stemming from a perceived lack of necessity (confirmation trap). Furthermore, companies may fall into the mistaken belief that their existing methods adequately address the requirements of this phase (anchoring).

Drawn to conclusions
Frequently, decision-makers will have preconceived notions regarding process deficiencies and skip a thorough systematic analysis. This approach can result in an insufficient understanding of the AS-IS scenario, thereby limiting insight into the overall situation and identifying bottlenecks and weaknesses irrelevant to the process (anchoring and confirmation trap). Additionally, having an initial notion could restrict the analyst's perspective and potentially result in the prioritization of a less important issue or bottleneck simply because other bottlenecks were not considered nor identified (overconfidence).

Pre-existing knowledge
Managers frequently make decisions for the (re)design process, given their past experiences, knowledge, reference solutions, or best practices that are well-known in the BPM field (anchoring, confirmation trap, status quo). If the implementation or the design of the process matches strongly with previous situations, the decision-makers tend to suggest the known design or implementation (focalism, ease of recall). In order to justify their choice, they might search for decision-relevant data that validates the aspects reinforcing their redesign selection. In other words, managers tend to prioritize information that aligns with their previous knowledge (ease of recall). Additionally, after the redesign or the implementation of the process is done, managers tend to wrongly believe they could have predicted the success or failure of the implementation retrospectively (overconfidence, hindsight and the curse of knowledge).

Influence of organizational factors
In the course of process monitoring, organizational elements like leadership, culture, and communication methods can sway the decision-making process. Additionally, decision-makers emphasize data that aligns with their existing convictions, potentially causing them to disregard essential insights and alternative viewpoints that would be relevant to the monitoring process (confirmation trap).

6 Conclusions and implications

Several studies in cognitive psychology implied that individuals are not perfectly rational and have cognitive limitations, and can cause biased decisions. Business process designers, business analysts, process owners, managers, and stakeholders must make a decision-making process, especially in every phase of the BPM life-cycle. However, BPM approaches and techniques on the life-cycle rarely address how human factors influence the BPM life-cycle phases and even less acknowledge cognitive biases on these human factors.

The present study found 42 articles related to the challenges of each stage of the BPM life-cycle, and only 28 were able to link with cognitive biases. These cognitive biases were taken from the managerial decision-making literature of Bazerman and Moore (2012). The authors have mainly identified 20 biases that may lead to lower-quality decisions, and not even half have been analyzed or acknowledged within the BPM life-cycle. Within this study, it was found that certain cognitive biases recurred across multiple stages of the BPM life-cycle. The confirmation trap, for instance, manifested throughout the entire life-cycle, while the anchoring bias appeared in the process discovery, process analysis, and process implementation phases. Similarly, overconfidence bias was evident in the process analysis and process redesign stages, and the ease of recall bias manifested in the process discovery and process implementation stages. Additionally, we were able to provide an overall linkage of some issues within the BPM life-cycle that might be influenced by cognitive biases on each specific phase. Overall these findings offer a good start for devising strategies to reduce or eliminate the influence of biases during decision-making processes, more specifically, within the BPM life-cycle phases. The initial step for any decision-maker should involve recognizing these biases within the process; such recognition can facilitate their more straightforward mitigation.

Furthermore, addressing cognitive biases within the BPM life-cycle, can significantly enhance operational efficiency and the overall decision-making process. By proactively identifying and mitigating the impact of cognitive biases, managers can improve the outcomes of each life-cycle phase they engage in, thus promoting increased efficiency and better results. This study helps in having a better understanding of where potential cognitive biases can occur within the BPM life-cycle. It should be noted that these findings present an initial stepping stone for potential investigations into the human factors that influence the BPM life-cycle. This study addresses a narrative literature review whose purpose was to find cognitive biases that might influence the BPM life-cycle. In order to address this, an indirect linkage had to be made with the issues, challenges, or proposals found in the studies. Since there was a gap in the literature about this topic, this approach is a good start for future researchers to delve into other cognitive biases or alternative perspectives on this intricate subject matter.

In future research, it is recommended to explore additional cognitive biases, including emotion and cognition collision, self-serving, and retrievability bias. These biases may have significant implications for the impact of BPM on the life-cycle. Given the considerable gap in the existing literature on this subject, this study aims to initiate a broader discussion concerning the influence of cognitive biases on the BPM life-cycle. The prevalence of these biases underscores their paramount importance in every decision-making instance confronted by managers.

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