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When participatory design meets data-driven decision making: A literature review and the way forward

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ABSTRACT

This study explores the impacts of participatory design (PD) on data-driven decision-making (DDDM) in organisations. Despite the extensive examination of PD and DDDM individually, there is a dearth of research in understanding their integration and their impact on decision-making processes in organisations. This research aims to fill this gap by investigating the potential impacts, challenges, benefits, and critical success factors associated with the incorporation of PD activities into DDDM. The study employs a systematic literature review methodology to provide a comprehensive understanding of the topic. The paper provides a research agenda for future researchers as well as discussing best practices for organizations seeking to optimise their data driven decision-making processes in a participatory manner. The research also discussed the ethical implications of data-driven decision-making. Ultimately, this research advances our understanding of how PD and DDDM can be effectively combined to achieve better decision-making outcomes.

1. Introduction

The rapid advancement of information technology and the exponential growth of data in recent years have given rise to a data-driven era where organizations increasingly rely on data to inform their decision-making processes (LaValle et al., 2010). The growing importance of data in decision-making has driven the evolution of various methodologies that aim to optimize the efficiency and effectiveness of these processes (Marsh et al., 2006). This research investigates the impacts of participatory design on data-driven decision-making (DDDM), focusing on the interplay between participatory decision-making (PDM), data-driven decision making (DDDM). In doing so, this research aims to provide a comprehensive understanding of how the integration of participatory design (PD) principles and practices can enhance the value of data-driven decision-making processes in organizations.

Data-driven decision-making has emerged as a critical aspect of organizational success in the 21st century (Provost & Fawcett, 2013a). This approach is characterized by the systematic use of data to guide actions, involving the collection, analysis, and interpretation of data to inform decisions (Kabadurmus et al., 2023; Provost & Fawcett, 2013b). The growing availability of data has revolutionized the way organizations approach decision-making, providing them with valuable information to make more informed decisions (McAfee et al., 2012). Furthermore, the emergence of Big Data and Data Analytics driven decision-making, a subfield of DDDM, refers to the practice of analysing massive volumes of structured and unstructured data to derive actionable insights that support strategic and operational goals (Chen et al., 2012) This development has further amplified the potential benefits of DDDM, allowing organizations to capitalize on the wealth of information contained in big data to drive better decision-making (Elgendy & Elragal, 2016).

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In parallel, participatory decision-making (PDM) has gained prominence as an approach that emphasizes the inclusion of stakeholders and end-users in the decision-making process (Kaner, 2014). This collaborative approach aims to ensure that the perspectives and needs of all parties are considered, leading to more effective and sustainable outcomes (Fung, 2015). The integration of PDM principles into data-driven decision-making processes has the potential to enhance decision quality by fostering collaboration, transparency, and shared ownership of decisions (O'Flynn, 2007). Moreover, PDM has been shown to result in more robust and context-sensitive decision-making processes, as the inclusion of diverse perspectives can help identify potential challenges, opportunities, and solutions that might not be apparent from the data alone (Irvin & Stansbury, 2004a).

Increasingly, organisations recognise that the most successful decision-making processes are those that are inclusive, taking into account the perspectives and insights of all stakeholders, including employees, customers, and other relevant parties. Herein lies the potential of Participatory Design (PD), a method that promotes active stakeholder involvement in designing solutions, which has shown promise in enhancing decision-making processes and outcomes (Björgvinsson et al., 2010).

While existing literature has extensively examined the individual aspects of participatory decision-making (PDM), and data-driven decision-making (DDDM), there is a dearth of research on understanding the integration of the two approaches and their impact on decision-making processes in organisation and corporate settings. Although some studies have briefly touched upon the potential synergies between PDM and DDDM (Brown, 2008; Fung, 2015), a comprehensive investigation of how participatory design principles can enable and enhance the effectiveness, efficiency, and sustainability of data-driven decision-making processes, particularly in the context of big data, remains largely unexplored.

This research gap presents an opportunity to examine the intersections of PDM and DDDM, and to identify the potential benefits, challenges, and critical success factors associated with their integration. Furthermore, this study will contribute to the development of best practices and guidelines for organizations seeking to optimize their decision-making processes by incorporating participatory design principles into their data-driven decision-making strategies. By addressing this research gap, the paper will offer valuable insights for both practitioners and scholars in the fields of participatory design, data-driven decision-making, and big data analytics, ultimately advancing our understanding of how these methodologies can be effectively combined to achieve better decision-making outcomes in the age of data.

This research is guided by the following research questions:

- What are the potential impacts of incorporating PD activities into the DDDM process?
- What are the challenges, barriers, benefits, and critical success factors associated with the application of PD in DDDM in organisations?

This research will explore the impacts of participatory design on data-driven decision-making in depth, investigating how PDM and DDDM can enhance the effectiveness, efficiency, sustainability in the decision-making processes in corporate environments. This research will also explore the effects of data-driven decision-making from an ethical consideration. To do so, the research will examine existing literature and empirical evidence from various industries and sectors, as well as explore the theoretical foundations and best practices in the fields of participatory design, data-driven decision-making, and big data analytics. Additionally, this study will delve into the potential barriers and challenges associated with integrating PDM and DDDM, aiming to identify strategies to overcome these obstacles and maximize the benefits of this approach, while being considerate of any ethical implications involved. By examining how PDM can fit into DDDM, this study aims to contribute to a deeper understanding of how participatory design can enhance the value of data-driven decision-making processes in organizations. Furthermore, this research will shed light on the critical success factors for implementing participatory design principles in data-driven decision-making contexts, providing actionable insights and recommendations for organizations seeking to optimize their decision-making processes in the age of data.

To summarise, the integration of participatory design principles into data-driven decision-making processes has the potential to transform the way organizations make decisions in the era of big data (Ho et al., 2019; Norori et al., 2021). By fostering a collaborative and inclusive environment, participatory design can help organizations harness the collective intelligence and expertise of their stakeholders to achieve more effective, efficient, and sustainable decision-making processes (Andrienko et al., 2007; Floridi et al., 2018). This research will provide a comprehensive examination of the impacts of participatory design on data-driven decision-making, ultimately contributing to the development of best practices and guidelines for organizations seeking to optimize their decision-making processes in the age of data.

The paper is structured as follows. Next section presents the overall methodology in which the systematic literature review was conducted. Section 3 outlines the results of the literature review, and the subsequent section (i.e., section 4) discussed the findings from the previous step. The paper ends with proposing a research agenda and some concluding remarks.

2. Methodology

This section delineates the methodology employed in this research, which is centred around a systematic literature review. A systematic literature review is a research method that enables comprehensive and unbiased collection, appraisal, and synthesis of existing research studies pertinent to a specific research question (Liberati et al., 2009). This approach ensures a broad spectrum of relevant research is considered, thereby providing a more reliable and holistic understanding of the research topic.

The systematic literature review methodology was chosen for this study because it allows for a rigorous and replicable approach to identifying, selecting, and critically appraising relevant research (Si et al., 2018). This systematic literature review follows the Webster and Watson (2002) approach. This approach involves providing a clear and detailed explanation of the methodology used in this study, ensuring transparency and reproducibility (Chaix-Couturier et al., 2000). This will allow other researchers to understand the process used to arrive at the findings of this study, and potentially replicate or build upon this research in the future. Additionally, this approach involves a concept-centric analysis and synthesis of the literature, which allows for a structured and comprehensive examination of the research topic. The methodology consists of five steps (Fig. 1), namely search strategy, study selection, data extraction & analysis, quality assessment and ethical considerations.

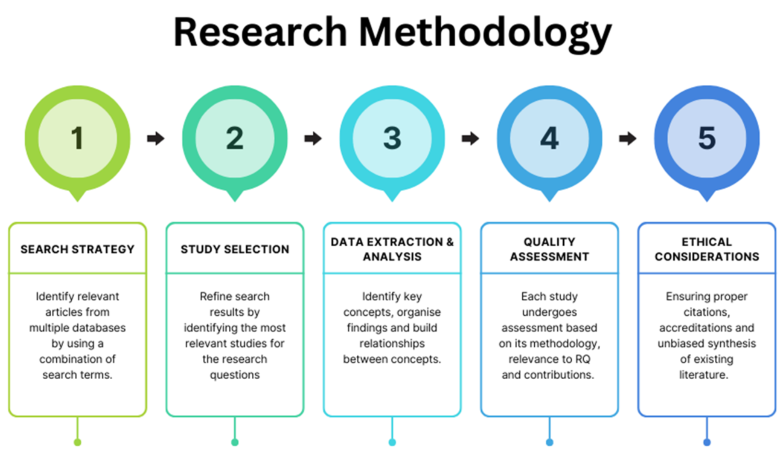

Fig. 1. Research Methodology steps

1.1 Search Strategy

The literature review adopted a systematic approach, aiming to identify relevant articles from multiple databases, including Scopus, Web of Science, Google Scholar, and IEEE Xplore (Bramer et al., 2017). The search process employed a combination of keywords and phrases related to the research topic, including "participatory decision-making," "data-driven decision-making," "participatory design," "big data decision-making," and "organizational decision-making" (Webster & Watson, 2002). The search terms were combined using Boolean operators (AND, OR) to ensure comprehensive coverage of the literature. This literature review will focus on quantitative and/or qualitative empirical studies, published peer reviewed journals and conference proceedings, written in English. There will be no specific timeframe for the sources involved in this research.

1.2 Study Selection

The initial search yielded a substantial number of articles. To streamline the search results and ensure relevance to the research questions (Papaioannou et al., 2016), a two-stage screening process was employed. This process involved the application of inclusion and exclusion criteria, followed by a detailed review of the remaining articles.

The inclusion criteria for the studies were as follows:

- Peer-reviewed articles or conference proceedings.
- Focused on participatory design, data-driven decision-making, or the synergies between the two approaches.
- Published in English.
- No timeframe restrictions.

Studies that did not meet the inclusion criteria or were found to be duplicates were excluded from the review (Moher et al., 2009). The remaining articles were then subjected to a two-stage screening process. In the first stage, the titles and abstracts of the articles were reviewed to assess their relevance to the research question. Articles that appeared to be relevant were then advanced to the second stage of screening (Bramer et al., 2017). In the second stage, the full texts of the remaining articles were reviewed in detail. This review aimed to confirm the relevance of the articles to the research question and to assess the quality and validity of the research. Articles that met the relevance criteria and demonstrated a high level of methodological rigor were included in the final review. This two-stage screening process ensured a thorough and systematic selection of studies for the literature review, minimizing the risk of bias and maximizing the relevance and quality of the included studies. A detailed table follows presenting major keywords used and specific about the numbers of results returned and reviewed.

In the preliminary stage of the literature review, a rigorous manual search was conducted across a diverse range of academic journals in the field. This exploratory search yielded 708 articles that met the initial inclusion criteria. The second phase involved deploying a carefully curated combination of keywords to execute searches in a set of widely recognised databases including Web of Science, EBSCO, PubMed, and IEEE Explore and Elsevier. These keywords were selected to accurately represent the scope of the research question and were customised according to the specific syntax and search filters of each database. This meticulous approach produced a list of 125 potential articles. Subsequent to the data collection, an evaluative phase was undertaken where each article was screened based on its title and abstract to determine its relevance to the research question. As a result of this examination, 85 articles were considered relevant and were therefore included in the literature review. Following this, the search strategy was extended to include a backward and forward citation search. This approach allowed us to locate articles that our selected articles cited (backward search) and articles that cited our selected articles (forward search). This citation tracking process proved fruitful, contributing an additional 12 articles to the literature base. In total, 97 articles have been exhaustively reviewed, each of which contributed to the formulation of the research conclusions. The literature review process thus demonstrated the breadth of existing knowledge on the topic and identified potential gaps that this research aims to address.

1.3 Data Extraction and Analysis

Once the relevant articles were selected, the data extraction process began by identifying and recording key information from each study, including authors, publication year, research methodology, and main findings (Arksey & O'Malley, 2005). This information was compiled into a summary table per concept, which facilitated the analysis and synthesis of the literature.

Following the Webster and Watson (2002) approach, the analysis and synthesis of the literature were structured around the key concepts identified in the research question: participatory decision-making, data-driven decision-making, and the integration of both approaches in organizational settings. The findings from the included studies were organized according to these concepts, and the relationships between the concepts were examined to identify potential synergies, benefits, challenges, and critical success factors associated with the integration of participatory design and data-driven decision-making processes (Webster & Watson, 2002).

In addition to the aforementioned steps, the Webster and Watson (2002) methodology emphasises the importance of understanding the theoretical foundations of the research topic, as well as identifying the gaps and opportunities for future research. As part of the literature review process, this study will also examine the theoretical underpinnings of participatory design, data-driven decision-making, and big data analytics, with the goal of establishing a solid conceptual framework for the research (Rowley & Slack, 2004). The literature review will not only explore the intersections and synergies between participatory decision-making and data-driven decision-making but also discuss the ethical considerations related to these approaches. Furthermore, potential barriers and challenges in integrating participatory design into data-driven decision-making processes will be addressed, with the aim of identifying strategies to overcome these obstacles and maximize the benefits of this integrated approach (Dixon-Woods et al., 2006). Finally, the literature review will identify areas where further research is needed to advance our understanding of how participatory design can enhance the value and effectiveness of data-driven decision-making processes in organisations (Arksey & O'Malley, 2005). By identifying these research gaps and opportunities, the study will contribute to shaping the future research agenda in the fields of participatory design, data-driven decision-making, and big data analytics, ultimately fostering a more comprehensive understanding of the potential synergies between these methodologies (Papaioannou et al., 2016).

In summary, the literature review conducted using the Webster and Watson (2002) methodology will provide a thorough and systematic investigation of the impacts of participatory design on data-driven decision-making processes in organizations. By examining the potential benefits, challenges, barriers, and critical success factors associated with the integration of participatory design and data-driven decision-making, this research will contribute to the development of best practices and guidelines for organizations looking to optimize their decision-making processes in the age of data.

2. Results

The literature review will provide an overview of the key concepts, theories, and empirical findings related to participatory decision-making (PDM), data-driven decision-making (DDDM), and Big Data / Analytics decision-making. Additionally, this section will examine the intersections and synergies between these methodologies and their potential benefits and challenges in the context of organizational decision-making processes.

2.1 Participatory Decision-Making

Participatory decision-making (PDM) is a collaborative approach that emphasizes in the active involvement of stakeholders and end-users in the decision-making process, ensuring that their perspectives and needs are considered when making decisions (Fung, 2015). The underlying premise of PDM is that involving a diverse group of individuals with varying perspectives and expertise can lead to better decision-making outcomes (Brown, 2008).

As the reviewed literature revealed, there are several key characteristics regarding to PDM. The first one is Inclusiveness**.** PDM aim is to include a diverse range of stakeholders and end-users in the decision-making process, ensuring that different perspectives and knowledge bases are represented (Ansell & Gash, 2008). Next is, Collaboration. PDM emphasizes collaborative problem-solving, with stakeholders working together to develop, evaluate, and implement solutions. Stakeholders' participation is welcomed and equally weighted. (Irvin & Stansbury, 2004a). The third on is, Empowerment. PDM seeks to empower participants by involving them in the decision-making process, providing them with the resources, information, and opportunities necessary to contribute meaningfully to the decision-making process (Fung, 2015). The fourth one is, Transparency. PDM promotes transparency by making the decision-making process open and accessible to all stakeholders, enabling them to understand and contribute in every step of the process (O'Flynn, 2007). Finally, there is Shared ownership. PDM fosters a sense of shared ownership over decisions, with stakeholders taking collective responsibility for the outcomes of the decision-making process (Quick & Feldman, 2011).

When it comes to practices in PDM they can be explained as stakeholder identification and engagement, deliberative processes, and collaborative problem-solving. Stakeholder identification and engagement is a crucial first step in PDM as it leads to identifying and engaging relevant stakeholders, including end-users, community members, experts, and organizational representatives. This process involves reaching out to potential stakeholders, communicating the goals and objectives of the decision-making process, and inviting them to participate (Ansell & Gash, 2008). Structured deliberative processes as often involved in PDM, such as workshops, focus groups, or public meetings, which provide stakeholders with opportunities to discuss and debate issues, share information, and develop shared understandings of the problems at hand (Fung, 2015). Collaborative problem-solving, as stakeholders in PDM work together to identify potential solutions, evaluate their feasibility and effectiveness, and develop implementation plans. This collaborative approach to problem-solving can lead to more innovative and effective solutions, as it draws on the collective knowledge and expertise of the stakeholders involved (Brown, 2008). Finally, feedback and iteration, as PDM processes often incorporate feedback loops, allowing stakeholders to evaluate the outcomes of decisions and make adjustments as needed. This iterative approach ensures that the decision-making process remains adaptive and responsive to the evolving needs and priorities of stakeholders (Irvin & Stansbury, 2004b).

Regarding the benefits of PDM, it may foster trust among stakeholders by involving them in the decision-making process, promoting transparency, and demonstrating a genuine commitment to addressing their concerns (O'Flynn, 2007). Another benefit is robustness in the decision-making process. PDM can lead to better decision-making outcomes by incorporating diverse perspectives, expertise, and knowledge, resulting in more well-rounded and context-sensitive decisions (Quick & Feldman, 2011). Improved implementation of decisions is an additional advantageous outcome of participatory decision-making. By involving stakeholders in the decision-making process, PDM can increase the likelihood of successful implementation of decisions, as participants develop a sense of shared ownership and responsibility for the outcomes (Ansell & Gash, 2008). This sense of ownership can motivate stakeholders to actively support and advocate for the decisions made, leading to smoother implementation and better overall outcomes (Fung, 2015). Enhanced social learning is the next. PDM processes facilitate social learning among stakeholders, as they engage in deliberative dialogues, exchange information, and negotiate different perspectives. This learning can enhance stakeholders' understanding of complex issues, as well as promote a more nuanced appreciation of the interests and concerns of other stakeholders (Irvin & Stansbury, 2004b). Moving on, PDM has the potential to address issues of equity and social justice by involving marginalized or underrepresented groups in the decision-making process, ensuring that their voices are heard, and their needs are considered. This promotes greater equity and social justice. Such an inclusive approach can contribute to more equitable and socially just outcomes (Brown, 2008). Finally, PDM offers enhanced legitimacy. Decisions made through PDM processes tend to enjoy greater legitimacy, as they are perceived to be more transparent, inclusive, and representative of the diverse interests and concerns of stakeholders. This increased legitimacy can lead to greater acceptance and support for decisions among the wider community (O'Flynn, 2007).

Strategic decision are the ones that can shape an organisation's long-term prospects in the marketplace, which can in turn determine the viability and sustainability of the business. Such decision making is usually derived from managerial teams, as it can be complex and can require joint contributions across multiple teams, departments and expertise (Hambrick, 2007).

Machine decision-making is an integral part of advanced technologies, driven predominantly by machine learning and artificial intelligence (AI) frameworks. It refers to the ability of a machine or algorithm to mimic the human decision-making process by analyzing complex datasets and choosing optimal outcomes (Russell, 2010).

Machine Learning (ML), a pivotal subset of AI, involves the use of algorithms that can learn from and make decisions or predictions based on data (Mitchell, 2007). ML employs diverse techniques, such as supervised, unsupervised, and reinforcement learning, to discern patterns in data, learn from them, and apply the learned knowledge to make informed decisions (Kelleher et al., 2020). These techniques vary based on the learning process and the type of data used, with potential implications for the resulting decision-making process. Advanced AI techniques such as deep learning and neural networks facilitate complex decision-making scenarios (Bengio et al., 2017). Deep learning, a subset of ML, utilises layered neural networks to analyse various factors and produce decisions. Mimicking the human brain's functionality, it can process a multitude of interconnected decisions, thereby dealing with more complex, real-world scenarios effectively. Despite their transformative potential, AI and ML systems have their limitations and raise crucial ethical questions. Factors such as data quality, inherent algorithmic bias, and privacy concerns can significantly impact machine decision-making (O'neil, 2017). It's also essential to consider how accountability is maintained when decisions are made by an algorithm (Bostrom & Yudkowsky, 2018).

In the context of participatory design, it's vital to understand machine decision-making. The participatory design approach posits that end-users, as non-technical experts, contribute to the design process in collaboration with technical experts (Sanders & Stappers, 2008). The resulting designs are, therefore, better tailored to user needs. Moreover, this approach could be instrumental in demystifying the machine decision-making process, making it more transparent, and ensuring it is guided by diverse human perspectives.

To summarize, it can be argued that participatory decision-making is likely to lead to better decisions. That is due to the fact that in the participatory decision-making process, stakeholders interact with each other in a manner that allows them to share their perspectives, influence and inspire others, voice their ideas and opinions and grow their skills. More specifically in corporate environments, PDM can also lead to increased job satisfaction and commitment as it instils a sense of belongingness through the collaborative process of PDM (Carmeli et al., 2009). Not only that but as noted by Sarin & McDermott in 2003, when senior management in organisations call teams and employees to collaborate and actively participate in problem solving activities, stakeholders involved usually try their best to come up with new ideas and thing outside of the box, which ends up enhancing problem solving and resulting in better decisions (Sarin & McDermott, 2003). While PDM offers several benefits, it is essential to recognize that its success depends on the effective design and implementation of participatory processes, as well as a genuine commitment to the principles of collaboration, inclusiveness, and shared ownership. Organizations and practitioners seeking to integrate PDM into their decision-making processes should carefully consider the context, resources, and stakeholder dynamics to ensure that participatory approaches are tailored to meet the specific needs and challenges of each situation (Fung, 2015; Quick & Feldman, 2011).

2.2 Data-Driven Decision-Making

Data-driven decision-making (DDDM) refers to the process of making decisions based on the analysis of data, rather than relying solely on intuition, experience, or anecdotal evidence (Provost & Fawcett, 2013a; Yu et al., 2021). As the availability of data has increased dramatically in recent years, DDDM has gained prominence in various sectors, including business, government, and non-profit organizations (Brynjolfsson et al., 2011; Gautam & Bhimavarapu, 2022). Big data decision-making is a subfield of DDDM that focuses on the analysis of massive volumes of structured and unstructured data to derive actionable insights for strategic and operational goals (Chen et al., 2012; Nisar et al., 2021). The emergence of big data has amplified the potential benefits of DDDM, as organizations can capitalize on the wealth of information contained in big data to drive better decision-making (Davenport & Patil, 2012; Osman et al., 2022). Tools and techniques used in big data decision-making include data mining, machine learning, and data analytics (Appelbaum et al., 2017). Studies have demonstrated the potential advantages of big data decision-making, such as improved efficiency, enhanced customer understanding, and increased innovation (LaValle et al., 2010; Wamba et al., 2015).

Regarding the characteristics of DDDM, Data-based decision-making is the first one. DDDM emphasizes the importance of using insights, derived from data, to inform decision-making processes. This approach helps to minimize the influence of biases, heuristics, or subjective opinions on decisions, leading to more objective and reliable outcomes (Provost & Fawcett, 2013a). Next is, Rigorous data analysis. DDDM requires the systematic collection, processing, and analysis of data to uncover insights, trends, and patterns that can inform decision-making. This rigorous approach to data analysis helps to ensure that decisions are based on a robust understanding of the underlying data (Chen et al., 2012; Nisar et al., 2021). The third one is, Continuous improvement. DDDM encourages organizations to continually monitor and evaluate the outcomes of their decisions, using data to identify areas for improvement and adjust their strategies accordingly. This continuous improvement mindset fosters a culture of learning and adaptation within organizations, as they strive to optimize their decision-making processes based on data-driven insights (LaValle et al., 2010). The last one is the fact that DDDM is linked to organisation processes**.** DDDM emphasizes the need to embed data-driven insights into the broader organizational processes and decision-making frameworks. This integration ensures that data-driven insights are not treated as standalone inputs but are instead used to inform and enhance existing decision-making processes (Kelleher et al., 2020).

According to the existing literature, we have identified some common practices in DDDM which can be grouped into several categories, such as data collection, data processing, and data analysis. With the first one being, Data Collection. DDDM requires the systematic collection of relevant data, which can come from a variety of sources, including internal organizational databases, customer transactions, social media, and publicly available datasets. Organizations must identify the most relevant data sources and develop strategies for collecting and storing this data in a structured and accessible format (McAfee et al., 2012). Data Processing is another key practice. Once data has been collected, it must be processed and cleaned to ensure its accuracy, completeness, and consistency. Data processing techniques, such as data validation, data imputation, and data transformation, can be used to address issues related to data quality and prepare the data for analysis (Chen et al., 2012). Data Analysis is next. The analysis of data is a vital step in the DDDM process, as it involves the application of statistical, machine learning, or artificial intelligence techniques to identify patterns, trends, and correlations within the data. These insights can then be used to inform decision-making, develop predictive models, or evaluate the effectiveness of existing strategies (Provost & Fawcett, 2013a). Last but not least, there is Visualisation and Communication. Effective DDDM requires the clear and compelling communication of data-driven insights to decision-makers and other stakeholders. Data visualization tools, such as charts, graphs, and dashboards, can be used to present complex data in a more accessible and intuitive format, facilitating the interpretation and understanding of data-driven insights (Kiron et al., 2013).

When it comes to the benefits of DDDM, improved decision-making accuracy is the first one. By basing decisions on empirical evidence derived from data, organizations can minimize the influence of biases, heuristics, or subjective opinions, leading to more accurate and reliable outcomes (Provost & Fawcett, 2013a). Another potential benefit is the resulting enhanced efficiency. Data-driven insights can help organizations identify inefficiencies in their processes, allocate resources more effectively, and optimize their operations, resulting in cost savings and improved productivity (LaValle et al., 2010). Greater agility and adaptability are two more advantages. DDDM enables organizations to respond more effectively to changes in their environment by leveraging data-driven insights to identify emerging trends, risks, or opportunities, and adjust their strategies accordingly (Brynjolfsson et al., 2011). Next, another benefit associated with DDDM is the improvements reflected on customer insights. Organizations can use data-driven decision-making to gain a deeper understanding of their customers, including their preferences, behaviours, and needs. This enhanced understanding can inform the development of more targeted and personalized marketing strategies, leading to increased customer satisfaction and loyalty (Kelleher et al., 2020). Moving on, DDDM leads to more informed risk management. DDDM allows organizations to make more informed risk assessments by using data to quantify and model potential risks and their impact on the organization. This data-driven approach to risk management can result in more effective mitigation strategies and improved organizational resilience (Chen et al., 2012). Last but not least, Innovation and competitive advantage. Organizations that effectively leverage data-driven insights can gain a competitive advantage by identifying new market opportunities, developing innovative products and services, predicting shifts in customer needs, identifying trends, and staying ahead of their competitors (McAfee et al., 2012).

Despite the potential benefits of data-driven decision-making, it is crucial to recognize that the successful implementation of DDDM depends on several factors, such as the quality and relevance of the data, the appropriateness of the analytical techniques used, and the organization's ability to integrate data-driven insights into its broader decision-making processes. Additionally, organizations must address potential ethical and privacy concerns related to the collection, storage, and use of data, ensuring that they comply with relevant regulations and industry standards (Kiron et al., 2013).

2.3 Application of PDM in DDDM Processes

The application of participatory decision-making (PDM) in data-driven decision-making (DDDM) processes can lead to more effective, transparent, and inclusive decision-making processes, as well as better outcomes for organizations and their stakeholders.

Improved Decision-Making Quality

By utilising the strengths and advantages of PDM in DDDM, organizations can make decision of higher quality. PDM ensures that diverse perspectives, experiences, and knowledge are incorporated into the decision-making process, while DDDM provides objective, evidence-based insights derived from data analysis. The integration of these two approaches can lead to more comprehensive, balanced, and nuanced decisions that account for both quantitative and qualitative factors (Bryson et al., 2014; Fung, 2015).

Increased Stakeholder Engagement and Trust

Data-driven insights can be used to support and inform participatory decision-making processes, enabling stakeholders to engage in more informed and evidence-based deliberations. The transparent use of data in PDM processes can enhance stakeholder trust and buy-in, as it demonstrates a commitment to objective, evidence-based decision-making rather than subjective or biased opinions (Klievink et al., 2017; Quick & Feldman, 2011). Consequently, this increased trust and active participation can lead to better implementation and outcomes for decisions made through PDM processes (Ansell & Gash, 2008).

Social Learning and Capacity Building

The application of DDDM into PDM processes can facilitate social learning and capacity building among stakeholders, as they engage in data-driven deliberations and develop a better understanding of the complexities, trends, and patterns underlying the issues they are addressing (Chen et al., 2012; Irvin & Stansbury, 2004b). This learning process can help stakeholders develop new skills and competencies related to data analysis, interpretation, and visualization, further enhancing their ability to participate effectively in decision-making processes.

Data-Driven Inclusivity

Incorporating DDDM into PDM processes can also contribute to greater inclusivity and equity in decision-making (Leicht-Deobald et al., 2019). By leveraging data-driven insights, organizations can identify and address potential barriers to participation, ensure that the needs and concerns of marginalized or underrepresented groups are considered, and develop more targeted and effective strategies for engaging these stakeholders in the decision-making process (Brown, 2008; McAfee et al., 2012).

Balancing the Challenges and Limitations

The use of PD activities into DDDM processes can help organizations balance the challenges and limitations associated with each approach. For example, PDM can address some of the ethical and privacy concerns related to the use of data in decision-making (Doorn, 2021) by ensuring that stakeholders have a voice in the development and implementation of data-driven strategies (Fung, 2015). Meanwhile, DDDM can help counter the potential biases, groupthink, or power imbalances that can emerge in participatory processes by providing objective, data-based insights to inform decision-making (Provost & Fawcett, 2013a). By integrating participatory decision-making and data-driven decision-making, organizations can harness the synergies between these two approaches to achieve more effective, transparent, and inclusive decision-making processes. This integration can help organizations address challenges and limitations associated with each approach while enhancing the overall quality of their decisions, stakeholder engagement, social learning, inclusivity, and long-term outcomes.

In conclusion, the integration of participatory decision-making and data-driven decision-making offers significant potential benefits for organizations and their stakeholders, as it can lead to more effective, transparent, and inclusive decision-making processes and outcomes. However, the successful implementation of this integrated approach requires careful consideration of the context, resources, and stakeholder dynamics, as well as a commitment to the principles of collaboration, shared ownership, and evidence-based decision-making.

2.4 Challenges and Barriers

Despite the potential benefits of incorporating participatory design principles in data-driven decision-making processes, organizations may face several challenges and barriers in achieving this integration.

Data Quality and Accessibility

One major challenge when applying participatory design activities in data-driven decision-making is ensuring the quality, relevance, and accessibility of the data used in the process. Stakeholders may not have access to the necessary data or may lack the skills and resources to collect, analyse, and interpret the data effectively (Chen et al., 2012). Furthermore, data may be subject to biases, errors, or omissions, which can compromise the quality of the decision-making process (LaValle et al., 2010).

Technical and Analytical Skills

The effective application of participatory design and data-driven decision-making requires stakeholders to possess a range of technical and analytical skills, including data collection, analysis, interpretation, and visualization. However, many end-users involved may lack these skills, leading to difficulties in effectively participating in data-driven decision-making processes (Klievink et al., 2017). As highlighted by Elgedy, Elragal and Päivärinta, there are immense challenges generating value and a deep understanding of data, especially when it comes to Big Data Analytics (BDA) (Elgendy et al., 2022). Organizations must invest in training that will allow their employees to grow their skills and competencies to actively participate in these processes.

Balancing Stakeholder Perspectives and Data-Driven Insights

Incorporating participatory design principles in data-driven decision-making processes requires organizations to balance the perspectives of employees with data-driven insights. This can be challenging, as stakeholders may have differing opinions, priorities, and interpretations of the data, leading to potential conflicts and disagreements during the decision-making process

(Bryson et al., 2014). Organizations need to develop mechanisms for managing these conflicts and ensuring that both stakeholder perspectives and data-driven insights are appropriately considered and incorporated into the decision-making process (Provost & Fawcett, 2013a).

Ensuring Privacy and Ethical Considerations

Data privacy is a paramount concern in data-driven decision-making. The use of data in decision-making processes raises concerns related to privacy and ethical considerations, particularly in cases where sensitive or personal information is involved (Fung, 2015). Organizations must be vigilant in adhering to relevant regulations, industry standards, and ethical guidelines to ensure that the data used in participatory design processes is collected, stored, and analysed in a responsible and transparent manner. This includes obtaining informed consent from stakeholders, implementing robust data security measures, and establishing clear guidelines for data usage (Curry et al., 2009; Valentine et al., 2018).

Ethical considerations extend beyond privacy. The use of data in decision-making processes raises questions about fairness, transparency, and accountability. For instance, organizations must ensure that their data-driven decision-making processes do not perpetuate existing biases or result in unfair outcomes. This requires a commitment to ethical data practices, such as ensuring the representativeness of data, interrogating the assumptions underlying data analysis techniques, and being transparent about the limitations of data-driven insights (Hodge et al., 2020). Moreover, the application of PD principles in DDDM processes can help address some of these ethical considerations. By involving stakeholders in the decision-making process, organizations can ensure that their data practices are not only technically sound but also socially acceptable and ethically justified. Participatory design can help foster a culture of ethical data use by promoting dialogue, mutual learning, and shared responsibility among all stakeholders (Berkes, 2004). However, the successful integration of PD activities and data-driven decision-making processes requires a proactive and ongoing commitment to privacy and ethics. Organisations must be prepared to continually reassess and update their data practices in response to evolving ethical standards, technological advancements, and stakeholder expectations. This includes investing in ethics education and training for all members of the organization, establishing clear ethical guidelines and accountability mechanisms, and fostering an organisational culture that values and prioritizes ethical data practices (Stilgoe et al., 2013).

In conclusion, ensuring privacy and ethical considerations is not just a regulatory requirement or a risk management strategy, but a fundamental aspect of responsible and effective data-driven decision-making. By incorporating PD activities and ethical data practices, organisations can navigate the complex ethical landscape of DDDM and harness the power of data in a manner that respects individual privacy rights, promotes fairness, and enhances social value (Cargo & Mercer, 2008).

Organizational Culture and Resistance to Change

Implementing an integrated approach to participatory design and data-driven decision-making may require significant shifts in organizational culture, processes, and structures (Quick & Feldman, 2011). Organizations may face resistance from stakeholders who are accustomed to traditional decision-making practices or who perceive data-driven decision-making as a threat to their authority or influence. To overcome this resistance, organizations must foster a culture of collaboration, openness, and shared ownership of the decision-making process, as well as provide the necessary support and resources to enable stakeholders to adapt to the new approach (Sleep et al., 2019).

2.5 Use Cases of DP in DDDM Processes

Participatory design activities have been increasingly recognised as a valuable approach in various fields, including policy making, healthcare, conservation, and welfare services. Existing literature suggests that there can be a variety of benefits when applying PD into DDDM.

For instance, in the realm of policy making, Shanley and López (2009) highlight the importance of including public users in the process of scientific research dissemination. They argue that the exclusion of these users from accessing research results is a systemic issue that hinders effective conservation and development. This suggests that the application of PD activities in data-driven decision-making can enhance the inclusivity and effectiveness of policies, particularly those related to natural resource management (Shanley & López, 2009). In healthcare, Matlock and Spatz (2014) discuss the concept of shared decision making (SDM), which involves patients in the decision-making process regarding their treatment. The authors note the challenges in operationalising SDM within routine clinical care, indicating the potential role of PD in facilitating this process. By incorporating PD activities, healthcare organisations can ensure that decisions are not only data-driven but also patient-centred (Matlock & Spatz, 2014). Moreover, in the field of conservation, Bennett et al. (2017) advocate for the mainstreaming of social sciences, including PD, in conservation science, practice, and policy. They argue that a more inclusive and integrative conservation science—one that includes both natural and social sciences—will lead to more ecologically effective and socially just conservation outcomes (Bennett et al., 2017). On the other hand, in the context of welfare services, Pedersen and Wilkinson (2018) discuss the emergence of a new model for the provision of welfare services in the digital society. They propose that data-driven management, as an integrated key element in a symbiotic co-evolution, creates participatory environments and spaces for the main actors associated with the provision of welfare services to citizens (Pedersen & Wilkinson, 2018). Lastly, Birhane (2021) discusses the negative consequences of algorithmic systems, particularly on marginalized communities, and calls for a critical examination of the field. This underscores the importance of PD in ensuring that data-driven decision-making processes are equitable and do not perpetuate existing injustices (Birhane, 2021). In conclusion, these use cases illustrate the potential of PD to enhance the effectiveness, inclusivity, and equity of data-driven decision-making processes in various fields. However, further research is needed to explore how PD can be best integrated into these processes and to identify the factors that can facilitate or hinder this integration.

2.6 Summary

Organisation can create a more effective, transparent, and inclusive decision-making environment by acknowledging and addressing the challenges and barriers in integrating participatory design principles with data-driven decision-making processes. This integration can help organizations balance the strengths and limitations of both approaches, ultimately leading to better decision-making processes and outcomes. This requires commitment and investment from organizations to support capacity building, privacy, and ethical considerations, and fostering a culture of collaboration and shared ownership of the decision-making process. In conclusion, integrating participatory design principles with data-driven decision-making processes can offer significant benefits for organizations and their stakeholders. However, organizations must be prepared to address the challenges and barriers that may arise during this integration, including issues related to data quality, stakeholder skills, balancing perspectives, privacy and ethics, and organizational culture. By proactively addressing these challenges, organizations can create a more effective, transparent, and inclusive decision-making process that leverages the strengths of both participatory design and data-driven decision-making.

3. Discussion

The discussion section presents a synthesis of the findings from the results, highlighting the key benefits, challenges, and strategies for applying participatory decision-making (PDM) to data-driven decision-making (DDDM) in organisations and corporate settings. Overall, this section provides a comprehensive understanding of the outcomes and implications of applying PD to the DDDM process.

The application of participatory decision-making (PDM) to data-driven decision-making (DDDM) processes provides an innovative perspective on new, all-rounded, decision-making processes and on their synergistic potential. Bryson et al. (2014) and Provost & Fawcett (2013) previously noted the complementary nature of these approaches. This research confirms their theories, demonstrating how PDM provides human insight and diversity of perspectives, while DDDM offers empirical, data-driven evidence. The result is a decision-making process that is both human-centred and evidence-based, leading to more informed and balanced decisions (Bryson et al., 2014; Fung, 2015). Using PDM practices in the DDDM process has been shown to improve the quality of decision-making outcomes. By incorporating diverse perspectives and experiences from stakeholders with objective, evidence-based insights from data analysis, organizations can make more comprehensive, balanced, and nuanced decisions (Bryson et al., 2014; Fung, 2015). For example, a study of participatory budgeting processes found that integrating data-driven insights into the decision-making process led to more equitable and effective allocation of resources (Ganapati & Reddick, 2018).

The significance of stakeholder engagement in the decision-making process is further amplified in this research. The findings corroborate Klievink et al. (2017) and Ansell & Gash's (2008) observations about the power of transparency in building trust and buy-in. The use of data-driven insights in a participatory manner ensures that the decision-making process is not only inclusive but also rooted in objective analysis, thereby fostering greater stakeholder trust and engagement. The use of data-driven insights in participatory processes can also empower stakeholders, as it provides them with information and tools to effectively advocate for their interests (Piotrowski & Van Ryzin, 2007). The literature suggests that the use of DDDM principles into PDM processes can facilitate social learning and capacity building among stakeholders. As stakeholders engage in data-driven deliberations, they develop a better understanding of the complexities, trends, and patterns underlying the issues they are addressing (Chen et al., 2012; Irvin & Stansbury, 2004b). This finding supports Irvin & Stansbury's theory about the learning potential inherent in PDM processes. This learning process can help stakeholders develop new skills and competencies related to data analysis, interpretation, and visualization, ultimately enhancing their ability to participate effectively in decision-making processes (Pardo & Scholl, 2002). Incorporating DDDM into PDM processes can also contribute to greater inclusivity and equity in decision-making. By leveraging data-driven insights, organizations can identify and address potential barriers to participation, ensure that the needs and concerns of marginalized or underrepresented groups are considered, and develop more targeted and effective strategies for engaging these stakeholders in the decision-making process (Brown, 2008; McAfee et al., 2012).

The research also underscores the challenges in integrating PDM and DDDM. Issues such as data quality, accessibility, and privacy (Fung, 2015; LaValle et al., 2010), balancing between stakeholder perspectives and data-driven insights (Bryson et al., 2014; Provost & Fawcett, 2013a), technical and analytical skills (Klievink et al., 2017), and organizational culture (Quick

& Feldman, 2011) emerge as significant challenges. This aligns with the cautionary tales from existing literature, adding empirical support to these theoretical considerations.

A major challenge when trying to encapsulate PDM in the DDDM process, is ensuring the quality, relevance, and accessibility of the data used in the process. Stakeholders may not have access to the necessary data or may lack the skills and resources to collect, analyse, and interpret the data effectively (Chen et al., 2012). Moreover, data may be subject to biases, errors, or omissions, which can compromise the quality of the decision-making process (LaValle et al., 2010). Organizations need to invest in improving data quality and accessibility to overcome these challenges. For PDM to enhance DDDM processes, stakeholders are required to possess a range of technical and analytical skills, including data collection, analysis, interpretation, and visualization. Many end-users involved may lack these skills, leading to difficulties in effectively participating in data-driven decision-making processes (Klievink et al., 2017; Rittel & Webber, 1973). Organizations must invest in training and capacity-building initiatives that allow their employees to develop the skills and competencies needed to actively participate in these processes (Pardo & Scholl, 2002).

The effort of applying PDM principles to DDDM processes requires organisations to balance the perspectives of employees with data-driven insights. This can be challenging, as stakeholders may have differing opinions, priorities, and interpretations of the data, leading to potential conflicts and disagreements during the decision-making process (Bryson et al., 2014). Organizations need to develop mechanisms for managing these conflicts and ensuring that both stakeholder perspectives and data-driven insights are appropriately considered and incorporated into the decision-making process (Provost & Fawcett, 2013a). The use of data in decision-making processes raises concerns related to privacy and ethical considerations, particularly in cases where sensitive or personal information is involved (Fung, 2015). Organisations must adhere to relevant regulations, industry standards, and ethical guidelines to ensure that the data used in PDM processes is collected, stored, and analysed in a responsible and transparent manner. This includes obtaining informed consent from stakeholders, implementing robust data security measures, and establishing clear guidelines for data usage (Valentine et al., 2018). Implementing an approach where PDM enhances DDDM may require significant shifts in organizational culture, processes, and structures (Quick & Feldman, 2011). Organizations may face resistance from stakeholders who are accustomed to traditional decision-making practices or who perceive data-driven decision-making as a threat to their authority or influence. To overcome this resistance, organizations must foster a culture of collaboration, openness, and shared ownership of the decision-making process, as well as provide the necessary support and resources to enable stakeholders to adapt to the new approach (Sleep et al., 2019).

In response to these challenges, organisations need a proactive, multi-faceted approach. This involves capacity building, especially in terms of technical and analytical skills (Klievink et al., 2017), adherence to privacy and ethical guidelines (Valentine et al., 2018), and fostering a culture of collaboration and shared ownership (Sleep et al., 2019). Such a strategy is consistent with the idea that successful application of PDM to DDDM demands a tailored approach, sensitive to an organization's unique context, resources, and stakeholder dynamics (Bryson et al., 2014). This section outlines four strategies that can be employed to address these challenges across a variety of sectors.

Firstly, Addressing Bias in Big Data and AI for Health Care. Bias in AI algorithms for health care can have catastrophic consequences by propagating deeply rooted societal biases. This can result in misdiagnosing certain patient groups, like gender and ethnic minorities, that have a history of being underrepresented in existing datasets, further amplifying inequalities. Open science practices can assist in moving toward fairness in AI for health care. These include participant-centred development of AI algorithms and participatory science; responsible data sharing and inclusive data standards to support interoperability; and code sharing, including sharing of AI algorithms that can synthesize underrepresented data to address bias (Norori et al., 2021). Secondly, Uniting Resilience Research and Practice with Inequalities Approach. The concept of resilience has evolved, from an individual-level characteristic to a wider ecological notion that takes into account broader person-environment interactions. This approach advocates for people facing embedded societal inequalities and focuses on challenging inequitable policy agendas; engaging in co-produced research containing socially transformative rather than solely personally transformative elements; facilitating supported agency and co-identifying and co-delivering responses to adversities (Hart et al., 2016). Thirdly, Fostering a Collaborative and Inclusive Environment. By fostering a collaborative and inclusive environment, participatory design can help organizations harness the collective intelligence and expertise of their stakeholders to achieve more effective, efficient, and sustainable decision-making processes (Bason, 2018). Finally, Integrating Participatory Design Principles. The integration of participatory design principles into data-driven decision-making processes has the potential to transform the way organizations make decisions in the era of big data (Madsen & Slåtten, 2013).

Implementing participatory design activities in the context of data-driven decision making involves a careful blend of collaborative activities and strategies that consider both the needs of the stakeholders and the technical aspects of the decision-making process. Starting with stakeholder identification. This process involves identifying all the stakeholders who will be affected by or have an impact on the decision-making process. This may include end-users, developers, business leaders, and possibly external stakeholders such as regulatory bodies or customers (Sanders & Stappers, 2008). In addition, organisation collaborative workshops, is another option. In collaborative workshops, all stakeholders can come together to discuss the decision-making process. These workshops can be used to outline the goals of the system, identify the kinds of data that will be used, and discuss any ethical considerations (Robertson & Wagner, 2012). Next is, interactive prototyping. The process of developing interactive prototypes of the decision-making system allows stakeholders to explore and provide feedback on its functionality. Prototypes can help stakeholders understand the impact of their input on the outcomes and enable them to suggest changes (Sanders et al., 2010). Moving on, there is iterative design and evaluation. The use of feedback from stakeholders can improve the DM outcomes, and then can further optimise the process of prototyping and evaluation. This iterative process allows for continuous refinement and ensures that the DM process evolves in line with the needs and expectations of its users (Muller, 2003). Training and education is another beneficial activity. Organisations can offer training sessions and educational materials to help stakeholders understand the underlying technology, its limitations, and how it makes decisions based on the data. This can empower them to engage more effectively in the design process and make more informed contributions (Muller, 2003). Finally, to reflect and learn is a valuable activity. After implementation, reflection sessions can be organised to learn from the process. This can provide valuable insights for future participatory design projects and can help to identify any further modifications that might be needed in the current system (Robertson & Wagner, 2012). By involving stakeholders in the design process, you can create data-driven decision-making systems that are more ethical, more effective, and more aligned with the real-world needs of the people who use them.

The increasing prominence of data-driven decision-making systems has been met with several challenges that underline the need for a participatory design approach. The complexity and opacity of the algorithms used in these systems often make the decision-making processes difficult for users to comprehend, resulting in a lack of trust (Mittelstadt et al., 2016). Furthermore, these algorithms are trained on existing data, which may inherently reflect historical or societal biases. As a result, decisions made by the system could perpetuate these biases, leading to unfair outcomes (O'neil, 2017). There's also the concern that these systems may overlook the nuanced human context in which decisions are made, causing the systems to neglect factors that aren't easily quantifiable or included in the dataset (Eubanks, 2018). Consequently, these decisions may be technically correct but contextually inappropriate. Lastly, ethical issues surrounding privacy, consent, and potential harm are heightened in data-driven decision-making systems due to the sensitive nature of the data being handled (Friedman & Nissenbaum, 1996). By implementing a participatory design approach, these challenges can be addressed. Engaging stakeholders in the design process leads to a more transparent, fair, and contextually aware system while also helping navigate the ethical challenges that arise, ensuring those impacted by the system have their voices heard.

In summary, this research elucidates the potential benefits and challenges of applying participatory design (PD) activities and data-driven decision-making (DDDM). It provides a theoretical understanding for understanding how these two approaches can complement and enhance each other, leading to more effective, transparent, and inclusive decision-making processes. However, creating new processes that involve PD actives and data insights is not without challenges. As this study shows, issues such as data quality, technical skills, stakeholder perspectives, privacy concerns, and organisational culture can create barriers to the successful application of this approach. Therefore, organisations need to adopt a proactive and multi-faceted strategy to address these challenges, which may involve capacity building, adherence to ethical guidelines, and fostering a culture of collaboration and shared ownership.

Future research should focus on developing and testing strategies for overcoming these challenges, as well as exploring how the benefits of this approach can be maximised across different organisational contexts. This could involve case studies, comparative analyses, and longitudinal studies to assess the long-term impact of applying PD activities to DDDM on decision-making processes and outcomes. Furthermore, as the field of data science continues to evolve, future research should also consider how emerging data analysis techniques and technologies, such as artificial intelligence and machine learning, can be incorporated into PDM and DDDM processes. Such research could offer new insights into how these advanced techniques can enhance decision-making processes, as well as the potential challenges and ethical considerations associated with their use.

In the end, the ultimate goal should be to continue refining and enhancing our understanding of how participatory decision-making activities can be applied to data-driven decision-making with the aim of delivering better decisions, outcomes, and value for organisations and their stakeholders. As this study demonstrates, the aforementioned approach offers significant potential benefits, but realizing these benefits requires ongoing research, experimentation, and learning (Provost & Fawcett, 2013a). In light of the potential of applying human-centred activities to data insights, it is crucial that organisations explore innovative strategies to effectively merge these approaches and overcome the inherent challenges. One area that requires further exploration is the design and use of digital platforms for facilitating participatory and data-driven decision-making. These platforms could potentially improve data accessibility, foster collaboration, and enable more transparent decision-making processes (Quick & Feldman, 2011). The effectiveness, usability, and impacts of such platforms should be the focus of future research efforts.

Additionally, the role of leadership and/or senior management in driving the efforts to incorporate PD into DDDM should not be overlooked. Transformational leaders who can cultivate a culture of collaboration, openness, and evidence-based decision-making will be instrumental in achieving successful integration (Sleep et al., 2019). More research is needed to understand the leadership behaviours and strategies that are most effective in promoting this approach.

Moreover, the potential impacts of this approach on various stakeholder groups, including employees, customers, and other external stakeholders, should be a key area of inquiry. While this study suggests that the application of PDM into DDDM can enhance stakeholder engagement and trust (Ansell & Gash, 2008), more empirical research is needed to understand the conditions under which these benefits are most likely to occur and how they can be maximised. The ethical implications of the approach also warrant further exploration. As organisations increasingly rely on data for decision-making, they must navigate complex ethical issues related to privacy, consent, and the use of personal information (Valentine et al., 2018). Future research should aim to develop ethical guidelines and best practices for incorporating PD into DDDM, to ensure that this approach is not only effective but also responsible and respectful of stakeholders' rights and interests.

In relation to the aforementioned points, the development of participatory data-driven platforms and tools represents a promising area of innovation and exploration. Such platforms could potentially democratize access to data, facilitate the active involvement of diverse stakeholders in decision-making, and foster a more transparent and accountable decision-making culture (Klievink et al., 2017). However, the design, implementation, and evaluation of these platforms present a complex set of challenges, requiring a multidisciplinary approach that integrates expertise in areas such as data science, human-computer interaction, and organizational behaviour. Future research should strive to generate insights and guidelines that can inform the development of such platforms and contribute to the evolution of best practices in this emerging field.

The role of education and capacity building in promoting the effective application of PDM into DDDM should also be an area of focus for future research and practice. As noted by Chen et al. (2012), the successful integration of these approaches requires stakeholders to possess a range of technical and analytical skills. Therefore, organizations need to invest in training and development programs that can enhance stakeholders' data literacy and their ability to engage effectively in data-driven decision-making. Evaluating the effectiveness of such programs, as well as identifying the specific competencies that are most important for participatory data-driven decision-making, can be a valuable area of inquiry for future research.

Finally, as Fung (2015) posits, the inclusion of PD activities into DDDM should be seen as an ongoing journey, rather than a destination. As such, it is important to develop mechanisms for continuous learning and improvement, such as feedback loops, monitoring and evaluation systems, and learning communities. This will enable organizations to continually refine their approach, adapt to new challenges and opportunities, and maximise the benefits of PD and DDDM.

4. Research Agenda

Despite the promising outlook, further research is warranted to understand the complexities involved in integrating PDM and DDDM. Future studies can investigate strategies for addressing the challenges identified in this research, explore the effectiveness of this integrated approach across different organizational contexts, and assess the long-term impact of such integration on decision-making processes and outcomes.

The research questions that guided this study were:

- What are the potential impacts of incorporating PD activities into the DDDM process?
- What are the challenges, barriers, benefits, and critical success factors associated with the application of PD in DDDM in organisations?

This first question aligns with the ongoing exploration of how participatory design can impact various fields. For instance, in the field of conservation, there is a growing recognition of the value of social sciences and calls for better engagement with the human element. The conservation social sciences can provide unique and important contributions to society's understanding of the relationships between humans and nature and to improving conservation practice and outcomes (Bennett et al., 2017).

The findings from this literature review and case studies have several implications for practice and future research. For practitioners, the results highlight the potential benefits of applying PDM to DDDM processes, as well as the challenges and strategies associated with this integration. By adopting the strategies outlined in this study, organisations can enhance the effectiveness and inclusivity of their decision-making processes, ultimately leading to better outcomes and greater stakeholder satisfaction (Ansell & Gash, 2008). For future research, this study underscores the need for further empirical investigation into the combined approach of PDM and DDDM. While the aforementioned findings provide valuable insights into the benefits, challenges, and strategies associated with this integration, more research is needed to explore these issues in greater depth and across a broader range of organizational contexts (Klievink et al., 2017; Provost & Fawcett, 2013a). Additionally, future research could investigate the long-term impacts of applying PDM to DDDM on organisational performance, stakeholder engagement, and social and environmental outcomes.

This second research question highlights the need for future studies to investigate strategies for addressing the challenges identified in this research, explore the effectiveness of this integrated approach across different organizational contexts, and assess the long-term impact of such integration on decision-making processes and outcomes. The following research directions proposes several areas for future study, aiming to deepen our understanding and enhance the application of this fusion, ultimately contributing to more effective, transparent, and inclusive decision-making within organizations.

Future research should delve deeper into the barriers and facilitators of applying PDM to DDDM. This could involve conducting case studies and interviews across diverse sectors, including public, private, and non-profit organisations. Understanding the common challenges and successful strategies across different contexts can help to develop a comprehensive framework for the application of PDM activities to DDDM. This research could build on existing theories of organizational change and innovation adoption, such as the Diffusion of Innovations theory (Orr, 2003). This research would benefit from a series of case studies and interviews across different sectors, including public, private, and non-profit organisations.

The influence of organisational culture and leadership on the successful implementation of PDM in DDDM processes warrants further investigation. Research should focus on identifying the leadership styles and cultural characteristics that foster this innovative decision-making approach. This includes developing a better understanding of the leadership styles and cultural characteristics that are most conducive to this new decision-making approach. In addition, it could involve applying established theories of leadership and organisational culture, such as Transformational Leadership theory (Bass & Riggio, 2006) and the Competing Values Framework (Cameron & Quinn, 2000), to the context of PDM and DDDM.

As DDDM often involves handling sensitive data, future research must address the ethical considerations and privacy concerns associated with this approach. This could involve developing best practices for data governance and creating an ethical framework to guide organisations. This research could draw on existing frameworks in the field of data ethics, such as the Fair Information Practice Principles (FIPPs) and the General Data Protection Regulation (GDPR). Moreover, it could also involve investigating best practices for data governance and creating an ethical framework to guide organisations in this new decision-making approach.

The transition to DDDM requires organizations to develop technical and analytical skills. Research into strategies for building these capacities, such as designing relevant training programs and fostering partnerships, will be crucial for the successful implementation of DDDM. This research could build on existing theories and models of organizational learning and capacity building, such as the Knowledge-Creating Company model (Nonaka & Takeuchi, 2007).

Lastly, it is essential to develop appropriate metrics and tools for evaluating the impact of PD activities on DDDM processes. Future research should focus on creating a balanced set of criteria to assess the performance and outcomes of this new decision-making approach. This could involve applying established frameworks for performance measurement and impact evaluation, such as the Balanced Scorecard (Kaplan & Norton, 2015) and the Logic Model (Kellogg, 2004). This will require the creation of a balanced set of criteria to assess the performance and outcomes of this new decision-making approach.

Additional research could investigate the long-term impacts of applying PDM to DDDM on organizational performance, stakeholder engagement, and social and environmental outcomes. This could involve longitudinal studies to track the effects of this integrated approach over time. The research could also explore how to sustain the benefits of PDM and DDDM in the face of changing organizational contexts and external environments.

Given the diversity of organizational contexts, comparative studies could provide valuable insights into how the integration of PDM and DDDM plays out in different settings. This could involve comparing different types of organizations (e.g., public vs. private, large vs. small) or different sectors (e.g., healthcare, education, technology). Such research could help to identify context-specific strategies and challenges, contributing to a more nuanced understanding of the integration of PDM and DDDM.

This research agenda aims to build on the work conducted in this study to further enhance our understanding and application of the fusion of PDM and DDDM, contributing to more effective, transparent, and inclusive decision-making within organisations.

5. Conclusion

Throughout this research, we have explored the impacts of Participatory Design (PD) and Data-Driven Decision-Making (DDDM), and how applying one to each other can lead to more effective, transparent, and inclusive decision-making processes within organisations. This journey has revealed significant potential benefits, but also complex challenges and barriers that need to be addressed to realise these benefits fully.

The fusion of PDM and DDDM presents a paradigm shift in traditional decision-making, offering a richer and more nuanced approach that balances the strengths and limitations of both approaches. It is a recognition that decision-making cannot be solely based on the quantitative insights derived from data analysis (DDDM), nor can it be solely dependent on the qualitative insights from participatory processes (PDM). Instead, there is a need to balance these two elements, ensuring that decision-making is both evidence-based and participatory, both objective and inclusive. This integrative approach to decision-making has the potential to transform organizations by improving the quality of decisions, fostering stakeholder engagement and trust, facilitating social learning and capacity building, and promoting inclusivity (Bryson et al., 2014; Fung, 2015). It offers a way of addressing complex and multi-faceted problems that cannot be solved through traditional decision-making approaches alone. As such, it is particularly relevant in today's increasingly complex, dynamic, and interconnected world, where organisations are often faced with challenges that require innovative and collaborative solutions.

However, the fusion of PDM and DDDM also presents a host of challenges and barriers, from ensuring data quality and accessibility, to building technical and analytical skills, balancing stakeholder perspectives and data-driven insights, addressing privacy and ethical considerations, and overcoming resistance to change in organisational culture (Chen et al., 2012; Klievink et al., 2017). Overcoming these challenges requires a proactive and strategic approach, as well as a commitment to continuous learning, adaptation, and improvement. It requires organizations to invest in capacity building, establish robust data governance structures, foster a culture of collaboration and shared ownership, and develop strategies for managing conflicts and balancing diverse perspectives. Moreover, this article has also highlighted the need for further research to deepen our understanding of applying PDM into DDDM, and to develop more effective strategies that are required when designing such decision-making processes. We have identified several areas for future research, including the role of leadership, the impact of regulatory and policy frameworks, and the methodological opportunities and challenges associated with participatory data-driven decision-making.

The insights gained from this work can provide a foundation for organisations to successfully navigate the complexities that arise from implementing the proposed approach. By employing the strategies and addressing the challenges outlined in this research, organisations can create a decision-making process that is not only more effective and efficient but also more inclusive and transparent. It is important to note that while implementing this approach may seem daunting, the potential benefits for organizations and their stakeholders are substantial (Bryson et al., 2014; Fung, 2015). The ethical considerations and privacy concerns associated with DDDM are another area of critical importance. Organisations must ensure they comply with all relevant laws and regulations, as well as uphold the highest standards of ethical conduct when handling data (Fung, 2015). This commitment to ethical and responsible data usage will be essential in maintaining stakeholder trust and support.

Finally, the culture of an organization plays a critical role in the successful incorporation of PD activities into DDDM. Organisations must foster a culture of collaboration, openness, and shared ownership, where stakeholders feel empowered to participate in decision-making processes and where data-driven insights are valued and understood (Quick & Feldman, 2011). This cultural shift may take time and require a significant amount of effort, but the potential rewards in terms of improved decision-making quality and stakeholder engagement are immense.

5.1 Contributions

The contributions of this study lie in three primary areas: theoretical understanding, methodological advancement, and practical implications.

Theoretical Understanding. This research contributes to the understanding of decision-making processes within organizations by bridging the gap between two well-established approaches: Participatory Decision-Making (PDM) and Data-Driven Decision-Making (DDDM). By combining these approaches, this study enhances theoretical understanding on decision-making that balances the strengths and limitations of both approaches. This approach extends existing theories of decision-making by recognising the importance of both evidence-based and inclusive decision-making, and by highlighting the potential synergies between PD and DDDM (Bryson et al., 2014; Fung, 2015; Klievink et al., 2017).

Methodological Advancement. This research also contributes to the methodological development in the field of decision-making research. It employed a mixed-methods approach, combining existing case studies, to investigate the impacts of PD and DDDM within organisations. This approach allowed for a more nuanced and holistic understanding of the phenomenon and offered insights into both the 'what' and the 'how' of the impacts. Furthermore, it highlighted the value of qualitative methods in decision-making research and provided a methodological blueprint for future studies in this area (Ansell & Gash, 2008).

Practical Implications. Beyond the academic realm, this research offers practical insights for organisations seeking to enhance their decision-making processes. It provides a roadmap for incorporating PD activities into DDDM and offers strategies for overcoming the challenges and barriers associated with this approach. It emphasises the need for a strategic and proactive approach, a commitment to continuous learning and adaptation, and a culture of collaboration and shared ownership (Matlock & Spatz, 2014). Moreover, it highlights the role of leadership, data governance, capacity building, and stakeholder engagement in facilitating the integration process (Sarin & McDermott, 2003).

By combining human-centric PD activities into the DDDM processes, this study provides a state-of-the-art analysis of the field. It goes beyond existing literature by offering insights into the incorporation of participatory design on data-driven decision-making and identifying research gaps that have not been thoroughly explored. Additionally, this research provides a set of research questions to stimulate further investigations such as, algorithm explainability, privacy and security, and legislative considerations. By presenting a unique and comprehensive perspective, this research contributes to advancing the understanding and application of Pd activities in DDDM, filling a crucial gap in the extant studies.

In sum, this study contributes to our understanding of decision-making processes within organisations, advances methodological approaches in decision-making research, and provides practical insights for organizations seeking to enhance their decision-making processes. It is our hope that these contributions will not only add to the body of knowledge in the field of decision-making research, but also inform and inspire future research and practice in this important area. Despite these contributions, it is important to acknowledge that this research represents only a small step in the journey towards a more comprehensive understanding of how PD activities can enhance and increase the effectiveness of DDDM. There is much more to be learned, and many more questions to be answered. As such, this research is not an end, but rather a starting point for further exploration and discovery. We hope that it will spark further interest and research in this important area and contribute to the ongoing evolution of decision-making theory and practice.

5.2 Limitations

This study was not far from limitations that should be considered when interpreting the findings. First, the literature review is primarily based on published academic articles, which may not fully capture the range of experiences and perspectives related to the integration of PDM and DDDM in practice. Future research could incorporate additional sources of information, such as grey literature, practitioner reports, and case studies, to provide a more comprehensive understanding of the topic. Second, this case study analysis is limited by the availability and quality of information about the specific cases. While efforts were made to select diverse and well-documented case studies, the findings may not be generalisable to all organisations or contexts. Additionally, this study does not delve into the individual steps involved in the decision-making process within organisations. The complexities and nuances of organizational decision-making, including the hierarchical dynamics, the roles of different stakeholders, and the unique organizational culture, are not directly addressed. While participatory design can have a broad impact on the decision-making process, a comprehensive understanding of how these specific organizational factors interact with and influence the process would require further research. Future research could expand the scope of case study analysis by examining additional cases and exploring the factors that contribute to successful application of PDM to DDDM in different settings. Finally, the study focuses on identifying the impacts of PD activities and DDDM as a means to enhance decision-making processes but does not examine the potential negative consequences or trade-offs associated with this approach. Future research could explore the potential downsides, such as increased complexity, decision-making paralysis, or the risk of misusing data in the decision-making process.

5.3 Summary

As researchers move forward, it is crucial to continue investigating and innovating in this area. The journey towards effective, transparent, and inclusive decision-making is a complex one, filled with potential hurdles and challenges. However, it is also a journey filled with great potential for creating more responsive, resilient, and equitable organizations. In the words of the renowned systems scientist Peter Senge (Peter, 1990), "The organizations that will truly excel in the future will be the organizations that discover how to tap people's commitment and capacity to learn at all levels in an organisation." This statement underscores the importance of fostering an environment where data-driven insights and participatory processes can thrive, leading to decisions that are not only effective but also deeply rooted in the collective wisdom and shared experiences of all stakeholders. In conclusion, this research has sought to shed light on the integration of Participatory Decision-Making and Data-Driven Decision-Making, highlighting the potential benefits, challenges, and strategies for successful implementation. We hope that this research will serve as a valuable resource for organizations seeking to enhance their decision-making processes and for scholars interested in further exploring this fascinating and important field.

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