**Analysis of the Drivers and Barriers Influencing Artificial Intelligence for Tackling** **Climate Change Challenges**

**Abstract**

Purpose: Facilities management (FM) organizations are pivotal in enhancing the resilience of buildings against climate change impacts. While existing research delves into the adoption of digital technologies by FM organizations, there exists a gap regarding the specific utilization of Artificial Intelligence (AI) to address climate challenges. This study aims to investigate the drivers and barriers influencing the adoption and utilization of AI by South African FM organizations in mitigating climate change challenges.

Design/Methodology/Approach: This study focuses on South Africa, a developing nation grappling with climate change's ramifications on its infrastructure. Through a combination of systematic literature review and an online questionnaire survey, data was collected from representatives of 85 professionally registered FM organizations in South Africa. Analysis methods employed include content analysis, Relative Importance Index (RII), and Total Interpretative Structural Modelling (TISM).

Findings: The findings reveal that regulatory compliance and a responsible supply chain serve as critical drivers for AI adoption among South African FM organizations. Conversely, policy constraints and South Africa's energy crisis emerge as major barriers to AI adoption in combating climate change challenges within the FM sector.

Originality/Value: This study contributes to existing knowledge by bridging the gap in understanding how AI technologies are utilized by FM organizations to address climate challenges, particularly in the context of a developing nation like South Africa. The research findings aim to inform policymakers on fostering a conducive environment for FM organizations to harness AI in fostering climate resilience in built assets.

**Keywords:** Artificial Intelligence, Barriers, Climate Change, Drivers, Facilities Management, Influencing.

# 1. Introduction

The effects of climate change globally remain evident as the incidence of storms, droughts, fires, and floods has intensified recently. Furthermore, shifts in global ecosystems have become prevalent, impacting the availability of natural resources and agricultural produce, which society depends on for its sustenance. Experts have warned of catastrophic consequences of climate change unless global greenhouse gas emissions are eliminated within 30 years (Berg and Lidskog, 2018). However, such emissions have continued to rise annually, despite the seeming urgency. Addressing climate change involves both mitigation and adaptation. These multifaceted challenges present opportunities for impact. Alarmed by rising global greenhouse gas emissions and their threat to societal progress, world leaders have placed climate change at the center of economic development discussions. The United Nations (UN) spearheads global efforts to manage carbon footprints, with the annual Conference of the Parties (COP) serving as a key platform for discussing solutions (Locke *et al.,* 2023). The UN's Sustainable Development Goals (SDGs), particularly SDG 13, address climate change and the potential solutions.

The built environment industry is a major contributor to greenhouse gas emissions, making them a target for carbon neutrality efforts (Awuzie and Moghayedi, 2024; Locke *et al.,* 2023). Buildings are responsible for 40% of global emissions and use over 36% of the world's energy (Tam *et al.,* 2023; Röck *et al.,* 2019), placing industry at the centre of seeking innovations to cut carbon emissions. Strategies like lean construction, sustainable materials, digitalization, and the circular economy (CE) are being implemented worldwide to decarbonize construction and buildings. Whilst adoption rates and purposes for adoption may vary, all these strategies hold promise for reducing carbon and greenhouse gas emissions. For instance, researchers have recommended digital technologies like AI to ameliorate the industry’s contribution towards climate change (Ma *et al.,* 2024; Moghayedi and Awuzie, 2023; Govindan, 2023; Tao *et al.,* 2023).

The Fourth Industrial Revolution (4IR) era has spurred the development of disruptive technologies (Ramakrishna *et al.,* 2020; Hopster, 2021). These technologies promise improved efficiency, sustainability, and profitability, ultimately transforming businesses and society (Hopster, 2021). While the built environment sector lags other sectors in technology adoption, it has made considerable progress in recent times. However, Facilities Management (FM), a subsector of the built environment that focuses on managing physical assets (Nielsen *et al.,* 2016) and user needs (Pinto *et al.,* 2023), is only just beginning to embrace these advancements. In this context, AI, as one of the most disruptive technologies of the 4IR, has become a transformative tool in the built environment, significantly enhancing FM by improving operational efficiency and promoting sustainability (Moghayedi *et al.,* 2024). Facilities within the built environment, such as buildings, constitute a significant share of global energy consumption and greenhouse gas emissions, underscoring the necessity for innovative solutions like AI. In FM, AI applications include energy management and optimization, where machine learning and predictive analytics help reduce energy consumption by adjusting HVAC systems based on real-time data (Gispert *et al.*, 2023; Kor *et al.,* 2023; Khan *et al.,* 2023). Additionally, predictive maintenance powered by AI allows for early detection of equipment failures, minimizing downtime and energy loss. AI also plays a crucial role in creating smart buildings through integration with IoT devices, optimizing lighting, HVAC, and other systems to reduce energy use (Richter *et al.,* 2023; Ghansah, 2024; Huotari *et al.,* 2024). Furthermore, AI aids in resource management by monitoring consumption and suggesting conservation measures, thereby enhancing overall sustainability. Its ability to simulate climate scenarios supports the design of climate-resilient buildings and adaptive management strategies (Srivastava and Maity, 2023). By leveraging AI, FM organizations can lower their environmental impact, align with global sustainability standards, and contribute to the fight against climate change thereby demonstrating the potential of AI in transforming the built environment for a sustainable future.

Studies show AI's significant potential to improve FM practices (Vaiste, 2020; Marzouk and Zaher, 2020; Atkin and Bildsten, 2017). The rising levels of AI adoption among FM organizations coincide with the development of smart buildings that anticipate user needs and make real-time adjustments (Ghansah, 2024; Windapo and Moghayedi, 2020). For instance, a facet of AI referred to as machine learning (ML) has emerged as a powerful tool for making progress in this regard. Accordingly, scholars have mentioned the need for its strategic deployment to combat climate change (Kor *et al*, 2023; Stein, 2020; Rolnick *et al.,* 2022). FM expertise is increasingly being seen as crucial for tackling sustainability challenges like climate change and resource management (Nielsen *et al.,* 2016; Opoku and Lee, 2022). The use of relevant technology like AI can make FM expertise more effective and efficient in addressing these challenges.

However, the rate of adoption and use of these technologies by FM organizations operating within Global South countries such as South Africa remains limited. South Africa’s FM sector remains the most technologically advanced compared to other countries in sub-Saharan Africa. This implies that the sector in the country has achieved considerable levels of technology adoption and utilization maturity leveraging digital technologies like AI. Whilst this can be considered an indication of the sector’s technological capacity, literature detailing the contribution of these technologies to the growing utility of the sector in South Africa remains limited. The country, just like other countries in sub-Saharan Africa, has continued to bear the brunt of climate change due to factors like non-resilient infrastructure among others. Efforts are ongoing to use legislation to curb carbon and greenhouse emissions in the country. Some of this legislation has focused on the need to curb energy consumption levels in built assets and to increase reliance on renewable energy sources (Moghayedi and Awuzie, 2023). These policies, particularly those targeting the built environment, have heightened the demand from clients for effective implementation of pro-sustainability FM practices based on an overt reliance on digital technologies. Extant literature has postulated the significant contributions AI can make in enhancing the quality of FM service offerings in this regard.

However, literature detailing the performance of the South African FM sector as it pertains to the adoption and use of AI in developing and implementing strategies that confer a high degree of resilience against climate change challenges on the built asset, are scant. Extant studies have focused on exploring the drivers and barriers to adopting digital technologies in FM (Moghayedi *et al*., 2024; Araszkiewicz, 2017), highlighting the potential benefits for improved FM practice (Pinto *et al.,* 2023; Hübner *et al.,* 2022; Marcinkowski and Gawin, 2020).

While existing studies have provided valuable insights, there remains a significant opportunity to specifically explore the adoption and use of AI-related solutions in FM for tackling climate change challenges. This study contributes towards building the body of knowledge relating to the use of AI in advancing innovative FM practice for the improvement of built environment resilience against climate change challenges, albeit with a particular focus on South Africa.

Accordingly, the study seeks to fill this gap by establishing the relationship between the drivers and barriers to the adoption and use of AI by South African FM organizations to achieve a climate-resilient built environment. As such, this study will seek to answer the following research questions:

1. What are the drivers and barriers influencing the successful adoption and use of AI by South African FM organizations for tackling climate change challenges?
2. What is the relationship between the various drivers influencing the successful adoption and use of AI by FM organizations for tackling climate change challenges?
3. What is the relationship between the various barriers negating the successful adoption and use of AI by FM organizations for tackling climate change challenges?

Articulating responses to these questions in this study will contribute to the deepening of the knowledge domain relating to the utility of AI in enabling FM organizations to combat climate change in the built environment. The paper provides a brief literature review in section 2 followed by an overview of the methods deployed for the study in section 3. Section 4 focuses on the presentation of the study’s findings in a three-stage manner and are discussed in section 5. Lastly, conclusions are provided in Section 6.

**2. Literature Review**

***2.1 Facility Management, Artificial Intelligence and Climate Change: Exploring the connections.***

FM is crucial for business success, employee well-being, and environmental sustainability (Ikuabe *et al.,* 2023; Opoku and Lee, 2022; Moghayedi *et al.,* 2024). The growing FM industry demands continuous improvement to provide organizations with a competitive edge (Araszkiewicz, 2017; Pinto *et al.,* 2023). Innovation in FM, particularly focusing on sustainable practices, remains vital (Opoku and Lee, 2022). AI is being explored to drive such innovation due to its ability to enhance other digital technologies (Herweijer *et al.,* 2018; Marinchak *et al.,* 2018) and support data-driven decision-making (Belhadi *et al.,* 2022). AI's market growth (Statista, 2024) reflects its rising importance. The technology utilizes complex algorithms to automate tasks requiring human-like intelligence and analyze massive datasets for real-time decision-making (Di Vaio *et al.,* 2022; Herweijer *et al.,* 2018; Marinchak *et al.,* 2018). This fosters a business model grounded in innovation and data-driven cultures (Chowdhury *et al.,* 2022), with the AI market expected to surge to $2 trillion by 2030 (Statista, 2024).

AI tools and techniques are pivotal in advancing operational efficiency, sustainability, and user experience within FM. They encompass a spectrum of advanced technologies designed to optimize facility operations and maintenance. The primary applications and significance of these AI techniques in FM are summarized in Table 1.

Table 1: Applications and significance of AI techniques in FM

|  |  |  |
| --- | --- | --- |
| **AI Technique** | **Applications in FM** | **Significance** |
| Machine Learning (ML) | Predictive maintenance, fault detection, energy optimization | Reduces downtime, optimizes energy use, enhances equipment lifespan |
| Natural Language Processing | User-system interactions, voice commands, text-based queries | Improves communication, enhances responsiveness, streamlines FM operations |
| Computer Vision | Visual inspection, security monitoring, occupancy analytics | Automates surveillance, detects anomalies, optimizes space utilization |
| Predictive Analytics | Forecasting trends in facility usage, energy demand, equipment | Enables proactive decision-making, optimizes resource allocation, improves operational efficiency |
| Internet of Things (IoT) | Real-time data collection and analysis, smart building operations | Enhances data-driven insights, enables autonomous adjustments for energy conservation and user comfort |

AI's potential in climate change mitigation is well-documented. Green et al. (2022) found that AI could optimize logistics and supply chains in FM, resulting in reduced transportation emissions. Additionally, AI has been instrumental in integrating renewable energy sources into building management systems. Ma et al. (2024) demonstrated how AI algorithms could manage the variability of renewable energy sources, ensuring a stable and efficient energy supply for buildings. AI-driven simulations and modeling have also been pivotal in designing sustainable buildings. Moghayedi et al., (2021) discussed how AI tools could simulate various design scenarios to optimize for energy efficiency, water usage, and overall environmental impact from the early design stages.

Specifically, AI-driven predictive maintenance has significantly reduced operational costs and energy consumption in buildings, as shown by Moghayedi et al., (2023), who demonstrated that AI models could predict equipment failures and schedule maintenance, enhancing equipment longevity and reducing downtime. Moreover, machine learning algorithms have optimized energy usage in buildings, with Ahmad et al., (2021) highlighting AI's role in real-time energy monitoring and automated HVAC adjustments, leading to substantial energy savings and reduced greenhouse gas emissions. Furthermore, AI has been utilized to analyze space utilization patterns, assisting FM organizations in optimizing the use of available space. Zhang et al. (2022) showed that AI tools could predict occupancy patterns and adjust environmental controls, improving both energy efficiency and occupant comfort.

Furthermore, AI's value in smart buildings extends to cognitive FM (Ghansah, 2024; Rjab et al., 2023; Xu et al., 2019), predictive CO2 emission monitoring (Gispert et al., 2023; Arsiwala et al., 2023). In light of the above, the utility of AI in enhancing FM operations, especially as it relates to combating climate change challenges in the built environment, cannot be overlooked. This has led to the advocacy for increased adoption of the technology in FM organizations across the world, South Africa inclusive.

***2.2 Drivers and barriers to the adoption and use of AI by FM organizations***

A plethora of factors have been identified as either enabling or hindering the successful adoption of digital technologies by FM organizations. However, existing studies predominantly focus on the general factors influencing digital technology adoption, with little emphasis on the specific factors affecting the adoption and use of AI to combat climate change. The integration of AI in FM to address climate change challenges is driven by various strategic and operational drivers. Although this study seeks to address this gap, it relies on the elicitation of these factors (drivers and barriers) as chronicled in the literature which influence the adoption of AI by organizations involved with the built environment sector including FM in the first instance.

***Drivers***

The integration of AI in FM to address climate change challenges is driven by various strategic and operational factors. These drivers not only promote the adoption of AI technologies but also enhance the overall efficiency and sustainability of FM practices. The drivers influencing the adoption and use of AI by FM organizations derived from the literature are summarized and coded in Table 2.

Table 2: Drivers influencing the adoption and use of AI by FM organizations for tackling climate change challenges

|  |  |  |
| --- | --- | --- |
| **Driver** | **Definition** | **Sources** |
| Community/End-user Engagement (D1) | This refers to the strategies and practices used to involve and interact with the communities or people who are ultimately affected by a product, service, program, or initiative. | 1, 2, 3 |
| Competitive Advantage and Innovation (D2) | This factor refers to a company’s ability to foster a culture of innovation whilst continuously seeking improvements to enable them to remain financially viable and achieve long-term success in the marketplace. | 4, 5, 6 |
| Corporate Social Responsibility (D3) | Corporate Social Responsibility (CSR) refers to a company's voluntary efforts to integrate social and environmental concerns into their business operations and interactions with stakeholders. | 7, 8, 9 |
| Data Driven Decision Making (D4) | This concept connotes a company’s ability to leverage relevant data to make better business decisions rather than relying solely on intuition or heuristics solely. | 10, 11, 12 |
| Enhanced Corporate Reputation as Sustainability Champion (D5) | This refers to the ability of companies to leverage sustainability as a powerful tool to enhance their reputation, attract stakeholders, and achieve long-term success. | 13, 14, 15 |
| Financial Incentives/Profitability (D6) | Financial incentives are rewards offered to individuals or groups to motivate them to perform certain actions or achieve specific goals. Profitability refers to a company's ability to generate a financial return on its investments. | 9, 16 |
| Health and Well Being of Employees (D7) | Employee health and well-being refers to the physical, mental, and emotional state of employees in the workplace. | 17, 18, 19, 20 |
| Investor Pressure (D8) | Investor pressure refers to the influence that investors (individuals or institutions who invest money in companies) exert on the companies they invest in | 21, 22 |
| Lifecycle Cost Savings (D9) | This refers to the total cost of ownership of an asset or system considered over its entire lifespan, not just the initial purchase price | 9, 23, 24 |
| Long-term Sustainability (D10) | This concept refers to the ability of a system (an ecological, social, or economic system) to meet the needs of the present without compromising the ability of future generations to meet their own needs. | 9, 25, 26 |
| Market Demand (D11) | This represents the collective desire and purchasing power of potential customers for a particular offering. | 11, 27 |
| Regulatory Compliance (D12) | Regulatory compliance refers to following the laws, regulations, and standards set forth by government agencies or industry organizations. | 28, 29 |
| Resilience and Adaptation (D13) | Resilience refers to the ability of a system to absorb disturbance, recover quickly, and continue functioning effectively in the face of change whilst adaptation focuses on the adjustments a system makes in response to changing conditions. | 30, 31, 32 |
| Resources Efficiency (D14) | Resource efficiency refers to using the Earth's resources wisely, minimizing waste, and getting the most benefit from what we use. | 3, 33 |
| Responsible Supply Chain (D15) | A responsible supply chain refers to managing the entire flow of goods and services in a way that considers not just economic factors, but also environmental and social responsibility. | 27, 34 |
| Risk Management (D16) | Risk management helps organizations identify and prioritize AI applications that offer the greatest potential benefit while minimizing potential downsides. | 9, 20, 24 |
| Stakeholder Expectations (D17) | Stakeholder expectation refers to the criteria by which a person or group (stakeholder) involved in a project, organization, or situation will judge its success. | 9, 20 |

*Sources: Li and Lu, 2021[1]; Klein et al., 2020 [2]; Herath and Mittal, 2022 [3]; Krakowski et al., 2023 [4]; Kinkel et al., 2022 [5]; Neumann et al., 2024 [6]; Mariani et al., 2023 [7]; Agudelo et al., 2023 [8]; Regona et al., 2022. [9]; Di Vaio et al., 2022 [10]; Cubric, 2020 [11]; Cao et al., 2021 [12]; Isensee et al., 2021 [13]; Yu et al., 2023 [14]; Goralski and Tan, 2020 [15]; Wamba-Taguimdje et al., 2020 [16]; Nazareno and Schiff, 2021 [17]; Braganza et al., 2021 [18];, Budhwar et al., 2022 [19]; Malik et al., 2021 [20]; Nguyen et al., 2022 [21]; Merhi and Harfouche, 2023 [22]; Zhang et al., 2022 [23]; Abioye et al., 2021 [24]; Goralski, and Tan, 2020 [25]; Nishant et al., 2020 [26]; Dora et al., 2022 [27]; Smuha, 2021 [28]; Almeida et al., 2022 [29]; Leal Filho et al., 2022 [30]; Belhadi et al., 2022 [31]; Stein, 2020 [32]; Neumann et al., 2024 [33]; Modgil et al., 2022 [34]; Campion et al., 2022 [35]; Alsheiabni et al., 2019 [36]; Kumar et al., 2021 [37]; Radhakrishnan and Chattopadhyay, 2020 [39]; Strohm et al., 2020 [40]; Hangl et al., 2023 [41]; Yang et al., 2024 [42]; Kar and Kushwaha, 2023 [43]; Misra et al., 2023 [44]; Blanco et al., 2018 [45]; Bettoni et al., 2021 [46]; Jöhnk et al., 2021 [47].*

According to Table 2, Community and End-user Engagement remains a pivotal factor, as involving affected communities and end-users fosters transparency, trust, and collaboration. Engaging these stakeholders ensures that AI-driven solutions are more effective and widely accepted, aligning with the interests and needs of those impacted by FM initiatives (Li and Lu, 2021; Klein *et al.,* 2020; Herath and Mittal, 2022). Competitive Advantage and Innovation remain crucial for organizations aiming to stay financially viable and achieve long-term success. AI adoption allows FM companies to streamline operations, reduce costs, and enhance service delivery, thereby gaining a competitive edge in the marketplace (Krakowski *et al.,* 2023; Kinkel *et al.,* 2022; Neumann *et al.,* 2024).

The role of Corporate Social Responsibility (CSR) is increasingly significant, as companies voluntarily integrate social and environmental concerns into their operations. AI technologies enable FM organizations to meet CSR goals by improving energy efficiency, reducing carbon footprints, and promoting sustainable practices (Mariani *et al.,* 2023; Agudelo *et al.,* 2023; Regona *et al.,* 2022). Data-Driven Decision Making enhances the effectiveness of AI applications in FM by leveraging relevant data for informed business decisions. This approach optimizes resource allocation, predicts maintenance needs, and improves overall operational efficiency (Di Vaio *et al.,* 2022; Cubric, 2020; Cao *et al.,* 2021). Companies that position themselves as sustainability leaders can benefit from an Enhanced Corporate Reputation as Sustainability Champions. AI supports this by enabling sustainable building operations and demonstrating a commitment to environmental stewardship, attracting stakeholders and ensuring long-term success (Isensee *et al.,* 2021; Yu *et al.,* 2023; Goralski and Tan, 2020). Financial Incentives and Profitability drive AI adoption in FM, as AI technologies can reduce operational costs, enhance energy efficiency, and provide a return on investment, making them financially attractive (Regona *et al.,* 2022; Wamba-Taguimdje *et al.,* 2020).

Ensuring the Health and Well-being of Employees is a critical driver. AI can improve indoor environmental quality, optimize workspace utilization, and enhance overall workplace conditions, contributing to the physical, mental, and emotional well-being of employees (Moghayedi *et al.,* 2024; Nazareno and Schiff, 2021; Braganza *et al.,* 2021; Budhwar *et al.,* 2022; Malik *et al.,* 2021). Investor Pressure significantly influences the adoption of AI technologies. Investors increasingly demand sustainable and innovative practices, prompting FM organizations to integrate AI to meet these expectations (Nguyen *et al.,* 2022; Merhi and Harfouche, 2023).

Lifecycle Cost Savings consider the total cost of ownership over an asset’s lifespan. AI optimizes maintenance schedules, extends asset lifespans, and reduces long-term costs, emphasizing the importance of cost-effective strategies (Regona *et al.,* 2022; Zhang *et al.,* 2022; Abioye *et al.,* 2021). AI supports Long-term Sustainability by enabling systems to meet present needs without compromising the future. This contributes to more sustainable building operations and long-term environmental and economic sustainability (Regona *et al.,* 2022; Goralski and Tan, 2020; Nishant *et al.,* 2020). Market Demand influences AI adoption as the collective desire for sustainable and efficient facilities grows. This demand motivates FM organizations to implement AI solutions that cater to customer preferences (Di Vaio *et al.,* 2022; Cubric, 2020).

Regulatory Compliance is essential, as AI helps FM organizations adhere to environmental regulations, reducing legal risks and enhancing sustainability (Smuha, 2021; Almeida *et al.,* 2022). AI enhances Resilience and Adaptation by enabling systems to absorb disturbances and adapt to changing conditions, ensuring continuous functionality in the face of climate-related challenges (Leal Filho *et al.,* 2022; Belhadi *et al.,* 2022; Stein, 2020). Resource Efficiency is imperative, as AI optimizes the use of resources, minimizing waste, and contributing to more sustainable FM practices (Herath and Mittal, 2022; Neumann *et al.,* 2024). Managing a Responsible Supply Chain with a focus on economic, environmental, and social responsibility drives AI adoption. AI enhances supply chain transparency and efficiency, ensuring responsible management practices (Dora *et al.,* 2022; Modgil *et al.,* 2022). Risk Management is crucial for identifying and prioritizing AI applications that offer significant benefits while minimizing potential risks. This enhances overall risk management strategies within FM (Regona *et al.,* 2022; Budhwar *et al.,* 2022; Abioye *et al.,* 2021). Finally, meeting Stakeholder Expectations is key, as AI enables FM organizations to meet and exceed these expectations, fostering stakeholder satisfaction and trust (Regona *et al.,* 2022; Budhwar *et al.,* 2022).

***Barriers***

The adoption and use of AI in FM for tackling climate change are influenced by various barriers, each posing unique challenges that organizations must navigate. The identified barriers are summarized and coded in Table 3.

Table 3: Barriers influencing the adoption and use of AI by FM organizations for tackling climate change challenges

|  |  |  |
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| Barrier | Definition | Sources |
| Customer/Client Acceptance (B1) | This connotes the ability of an organization to secure the buy-in of its clients and customers concerning its product or services offering. | 20 |
| Data Privacy, Responsibility and Security Concerns (B2) | the right of individuals to control their personal information, ethical obligations of organizations that collect, store, and use personal information, technical and organizational measures taken to protect personal information from unauthorized access, use, disclosure, disruption, modification, or destruction. | 35, 36 |
| Inadequate Infrastructure: Legacy Systems and Infrastructure (B3) | Inadequate infrastructure, specifically in the form of legacy systems and infrastructure, refers to outdated technological components that hinder a business's ability to function efficiently and adapt to changing needs. | 20, 36, 37 |
| Initial Cost (B4) | Initial cost refers to the upfront expense incurred when acquiring an asset, bringing it to a ready-to-use state. | 9, 20, 24 |
| Lack of Awareness and Education (B5) | Lack of awareness and education refers to a situation where people are not informed or knowledgeable about a particular topic, issue, or concept. | 3, 9, 20, 24, 38, |
| Lack of Incentives (B6) | Lack of incentives refers to a situation where there is an absence of motivators that encourage people or organizations to take a particular action. | 3, 9, 39 |
| Lack of Skills and Proper Training (B7) | Lack of skills and proper training refers to a situation where individuals or a workforce lack the necessary knowledge, abilities, and experience to perform a job effectively. | 20, 24, 40 |
| Market Immaturity (B8) | Market immaturity refers to a stage in the lifecycle of a product or service category where the market itself is new or unproven. | 20, 41, 42 |
| Market Uncertainty (B9) | Market uncertainty refers to the unpredictability of factors that can significantly influence market conditions and, consequently, the profitability of businesses. | 20, 39, 43 |
| Measurement and Reporting Challenges (B10) | Measurement and reporting challenges are obstacles faced by organizations in accurately assessing and communicating their performance or the impact of their initiatives. | 9, 20, 40 |
| Regulatory and Policy Constraints/Barriers (B11) | Regulatory and policy constraints are limitations imposed by government regulations and policies that restrict the activities of businesses and individuals | 28, 36 |
| Resistance to Change (B12) | Resistance to change is the reluctance of people or organizations to adapt to new ways of doing things. | 36, 40, 43 |
| Resource Constraints (B13) | Resource constraints refer to limitations or restrictions on the availability of resources essential for achieving a particular objective or completing a task. | 3, 9, 20 |
| Risk Aversion (B14) | Risk aversion refers to the tendency of people or organizations to prefer certainty over uncertainty, even if the uncertain option has a potentially higher payoff. | 44 |
| Short-term Focus (B15) | Short-term focus refers to prioritizing immediate results and goals over long-term benefits and objectives. | 9, 20, 24, 45 |
| Slow/Low Return on Investment (B16) | A low return on investment (ROI) refers to a situation where the gain or benefit earned on an investment is relatively small compared to the initial cost or effort put in. | 36, 43, 46 |
| Technical Complexity (B17) | Technical complexity refers to the difficulty of understanding, designing, implementing, and maintaining a system or process. | 20, 40, 47 |
| Vendor Lock-In (B18) | Vendor lock-in, also known as proprietary lock-in or customer lock-in, refers to a situation where a customer becomes dependent on a single vendor for a product or service. This dependence makes it difficult and costly for the customer to switch to a different vendor, even if there might be better alternatives available. | 41 |
| Energy Crisis (B19) | An energy crisis is a situation where there is a shortage or disruption in the supply of energy resources, leading to widespread price increases and economic hardship. | Added by participants |

*Sources: Li and Lu, 2021[1]; Klein et al., 2020 [2]; Herath and Mittal, 2022 [3]; Krakowski et al., 2023 [4]; Kinkel et al., 2022 [5]; Neumann et al., 2024 [6]; Mariani et al., 2023 [7]; Agudelo et al., 2023 [8]; Regona et al., 2022. [9]; Di Vaio et al., 2022 [10]; Cubric, 2020 [11]; Cao et al., 2021 [12]; Isensee et al., 2021 [13]; Yu et al., 2023 [14]; Goralski and Tan, 2020 [15]; Wamba-Taguimdje et al., 2020 [16]; Nazareno and Schiff, 2021 [17]; Braganza et al., 2021 [18];, Budhwar et al., 2022 [19]; Malik et al., 2021 [20]; Nguyen et al., 2022 [21]; Merhi and Harfouche, 2023 [22]; Zhang et al., 2022 [23]; Abioye et al., 2021 [24]; Goralski, and Tan, 2020 [25]; Nishant et al., 2020 [26]; Dora et al., 2022 [27]; Smuha, 2021 [28]; Almeida et al., 2022 [29]; Leal Filho et al., 2022 [30]; Belhadi et al., 2022 [31]; Stein, 2020 [32]; Neumann et al., 2024 [33]; Modgil et al., 2022 [34]; Campion et al., 2022 [35]; Alsheiabni et al., 2019 [36]; Kumar et al., 2021 [37]; Radhakrishnan and Chattopadhyay, 2020 [39]; Strohm et al., 2020 [40]; Hangl et al., 2023 [41]; Yang et al., 2024 [42]; Kar and Kushwaha, 2023 [43]; Misra et al., 2023 [44]; Blanco et al., 2018 [45]; Bettoni et al., 2021 [46]; Jöhnk et al., 2021 [47].*

Going by the contents of Table 3, it can be seen that the acceptance of AI technologies by customers and clients constitutes a significant barrier. Gaining buy-in from these stakeholders is crucial, as resistance or hesitance can significantly impede the implementation of AI-driven solutions. This challenge underscores the importance of demonstrating the tangible benefits of AI to build trust and secure commitment from all involved parties (Malik *et al.,* 2021).

Data privacy, responsibility, and security concerns are paramount when integrating AI. Ensuring the protection of personal information and adhering to ethical standards in data handling are significant hurdles. Organizations must implement robust measures to safeguard data and comply with regulatory requirements, thereby building trust with their stakeholders (Campion *et al.,* 2022; Alsheiabni *et al.,* 2019). Similarly, outdated infrastructure, including legacy systems, can severely limit the ability to adopt and efficiently use AI. Modernizing these systems is often a complex and costly endeavor, requiring substantial investment and planning (Malik *et al.,* 2021; Alsheiabni *et al.,* 2019; Kumar *et al.,* 2021). The initial cost of acquiring and implementing AI technologies is another substantial barrier. High upfront expenses can deter organizations, particularly those with limited budgets, from investing in AI solutions (Regona *et al.,* 2022; Malik *et al.,* 2021; Abioye *et al.,* 2021). This financial challenge is compounded by a lack of awareness and education about AI and its potential benefits. Educating stakeholders is essential for fostering acceptance and ensuring successful implementation (Herath and Mittal, 2022; Regona *et al.,* 2022; Abioye *et al.,* 2021; Radhakrishnan and Chattopadhyay, 2020).

In addition to financial and educational barriers, a lack of incentives can hinder AI adoption. Without sufficient motivators, such as financial rewards or regulatory benefits, organizations may lack the drive to invest in AI technologies (Herath and Mittal, 2022; Regona *et al.,* 2022; Radhakrishnan and Chattopadhyay, 2020). Furthermore, the absence of skilled personnel and adequate training programs hampers the effective use of AI in FM. Investing in training and development is necessary to equip the workforce with the required knowledge and skills (Malik *et al.,* 2021; Abioye *et al.,* 2021; Strohm *et al.,* 2020). The immaturity and uncertainty of the market for AI technologies in FM also poses significant challenges. As AI technologies are often new and unproven, organizations may hesitate to adopt them due to doubts about their effectiveness and the unpredictable market conditions that can impact profitability (Malik *et al.,* 2021; Hangl *et al.,* 2023; Yang *et al.,* 2024). Additionally, difficulties in accurately measuring and reporting the performance or impact of AI initiatives can hinder adoption. Developing robust measurement frameworks is crucial to address these challenges (Regona *et al.,* 2022; Malik *et al.,* 2021; Strohm *et al.,* 2020).

Regulatory and policy constraints further complicate the adoption of AI. Navigating these constraints requires strategic planning to ensure compliance and avoiding potential legal issues (Smuha, 2021; Alsheiabni *et al.,* 2019). Organizational and individual resistance to change is another common barrier. Effective change management strategies are needed to overcome this reluctance and facilitate the adoption of new technologies (Alsheiabni *et al.,* 2019; Strohm *et al.,* 2020; Kar and Kushwaha, 2023). Resource constraints, including limited availability of financial, human, and technological resources, can also impede the adoption of AI. Efficient resource management and allocation are essential to address these limitations (Herath and Mittal, 2022; Regona *et al.,* 2022; Malik *et al.,* 2021). Additionally, risk aversion, or the tendency to avoid uncertain outcomes, can prevent organizations from investing in innovative AI solutions, even if they have potential higher payoffs (Misra *et al.,* 2023).

A short-term focus on immediate results over long-term benefits can further deter investment in AI, which often requires substantial initial investment with delayed returns (Regona *et al.,* 2022; Malik *et al.,* 2021; Blanco *et al.,* 2018). Moreover, the inherent technical complexity of AI systems demands specialized knowledge for their design, implementation, and maintenance, presenting another significant barrier (Malik *et al.,* 2021; Strohm *et al.,* 2020; Jöhnk *et al.,* 2021). Lastly, vendor lock-in, where dependence on a single vendor creates challenges such as high switching costs and limited flexibility, can hinder AI adoption. Organizations need strategies to mitigate the risks associated with vendor lock-in to maintain operational flexibility and avoid being tied to potentially suboptimal solutions (Hangl *et al.,* 2023).

Although the drivers and barriers influencing the adoption and utilization of AI in FM practice have been elucidated in preceding sections, studies investigating the relationship between these factors, and the influence thereof on the deployment of this technology for improving the contributions of contemporary FM practice towards engendering a climate-resilient built environment remain scant. This study seeks to address this gap, with particular focus on South African FM organizations.

# 3. Methodology

This study employed a sequential mixed-method research design to gain an understanding of the influence of drivers and barriers on adoption of AI by FM organizations to tackle the climate change in South Africa. The research participants were FM organizations registered with the South African Facilities Management Association (SAFMA).

Due to the limited population size of this study, consisting of 85 FM organizations registered with SAFMA, the Total Population Sampling (TPS) technique was employed to enhance the study's validity (Asiamah *et al.,* 2017). TPS includes the entire population of interest in the research, meaning all FM organizations registered with SAFMA participated in the study, thereby facilitating a comprehensive approach to participant recruitment and ensuring the acquisition of dependable data from all well-informed and experienced FM organizations in South Africa. The advantages of TPS justify its use in this study. Since all registered FM organizations are included, there is no sampling error, leading to highly accurate results that truly represent the entire population. Additionally, there is no chance of bias being introduced during the sample selection process, as the entire study population is included. By incorporating all registered FM organizations, the study gains a comprehensive localized understanding of the drivers and barriers to AI adoption and their level of influence on climate change mitigation (Asiamah *et al.,* 2017).

A three-stage approach, as depicted in Figure 1, was implemented to accomplish the study’s objectives.

Figure 1. Research methodology protocol

***Stage One:*** *Identification of Drivers and Barriers influencing adoption of AI.*

In this stage, the main drivers and barriers influencing the adoption of AI in built environment organizations were identified from the literature. Relevant studies were systematically sourced from various scientific databases using keywords such as “drivers,” “barriers,” “built environment,” “organization,” and “AI.” 47 documents were selected based on their relevance. These documents underwent a thorough content analysis, focusing on four main themes: “drivers”, “barriers”, “AI”, and “climate change”. This comprehensive scrutiny led to the identification of 17 key drivers and 18 significant barriers influencing AI adoption in built environment organizations. The analysis involved systematically coding and categorizing information from the documents to uncover patterns and themes relevant to AI adoption. The identified drivers include factors such as competitive advantage, innovation, and resource efficiency, which promote the integration of AI technologies. These drivers highlight the potential benefits of AI, such as enhanced operational efficiency, cost reduction, and improved service delivery. Conversely, the barriers encompass challenges like data privacy concerns, high initial costs, and technical complexity. These barriers underscore the difficulties organizations face in implementing AI solutions, such as the need for substantial investments, the complexity of integrating new technologies with existing systems, and the importance of maintaining data security and privacy. By categorizing and analyzing these drivers and barriers, the study provides a nuanced understanding of the factors that facilitate or hinder AI adoption in the built environment. This detailed examination helps in formulating targeted strategies to address the challenges and leverage the opportunities presented by AI, ultimately contributing to more effective and sustainable practices in FM and related fields. These drivers and barriers, alongside their sources, as presented in Tables 2 and 3, constituted an initial inventory for examining the factors influencing the adoption and use of AI by FM organizations for tackling climate change challenges.

***Stage Two:*** *Validating Drivers and Barriers*

The main goal of this stage was to validate and contextualize drivers and barriers influencing AI adoption within South African FM organizations. A semi-structured online questionnaire was used to validate the identified drivers and barriers. The questionnaires were distributed to every FM organization registered with SAFMA. Competent members from these organizations were requested to assess and rank these drivers and barriers using a 5-point Likert scale, ranging from "highly relevant" to "not relevant at all," to express the significance of each driver and barrier within their organizations. Participants were also encouraged to provide reasons and justifications if they deemed any drivers or barriers irrelevant. Additionally, participants were invited to leverage their professional experience and identify any additional drivers or barriers relevant to the local context and conditions of South Africa that may not have been addressed in the existing literature.

After completing the initial round of primary data collection, it was clear that only 22 out of 85 FM organizations had adopted AI in some form, yielding an adoption rate of 26%. As a result, these 22 FM organizations constituted the sample size for this study. All respondents who participated in the study unanimously agreed that the identified drivers and barriers influencing AI adoption for tackling climate change challenges were relevant and valid in their respective companies. However, the majority of participants (95.2%) added the national energy crisis as barrier 19 (B19) to adopting AI.

***Stage three****: Evaluating the influence of drivers and barriers on adoption of AI.*

The objective of this stage was to quantify the positive and negative level of influence of each driver and barrier on AI adoption for tackling climate change challenges. A logical condition was employed in the online questionnaire to exclusively gather information on the level of influence in the second part from FM organizations that have already adopted AI. This approach ensures the collection of actual data rather than perceptions. The 2nd part of the questionnaire required participants from FM organizations which had adopted AI to assess the influence of these drivers and barriers using a five-point Likert scale, where response options ranged from "very low influence" (1) to "very high influence" (5). A quantitative analysis of the data collected from 22 FM organizations was performed using the Relative Importance Index (RII) to quantify the importance of each driver and barrier. The RII was computed using Equation (1):

RII = (ΣW) / (N × A)

*Where:*

*W denotes the weight assigned to each variable by respondents, ranging from 1 to 5.*

*N represents the total number of respondents, with A indicating the highest weight, set at 5.*

The RII value ranges from 0% to 100%, with higher values indicating stronger factor influence. These values are classified into five levels of influence, encompassing both positive and negative impacts:

High (H): RII ≥ 80%

Medium-High (M–H): 80% > RII ≥ 60%

Medium (M): 60% > RII ≥ 40%

Medium-Low (M–L): 40% > RII ≥ 20%

Low (L): 20% > RII > 0%

The RII method is chosen for its robustness in comparative analysis, specifically for quantifying and ranking the relative importance of various factors based on survey data. This method is particularly useful in assessing the influence of different drivers and barriers, making it essential for this study. By identifying and prioritizing key drivers and barriers, RII contributes significantly to the research objectives, aiding in the formulation of targeted strategies for AI adoption in FM organizations.

***Stage Four:*** *Establishing Interrelationships*

The goal of this phase was to comprehensively examine and define the contextual connections among the identified drivers and barriers, prioritizing them hierarchically and logically using Total Interpretive Structural Modelling (TISM). This was expected to determine critical drivers and barriers influencing the adoption of AI for tackling climate change challenges. To facilitate this process, a 3rd part of the questionnaire was designed to determine the potential relationships among the contextualized drivers and the contextualized barriers influencing adoption of AI. The logical condition utilized to only the FM organizations adopted AI identifying and deliberating possible contextual relationships existing between the 17 drivers and 19 barriers.

The questions are structured based on the four possible relationships, factor i will influence factor j, factor j influence factor I, factor i and j influence each other and factor i and j are unrelated. Their viewpoints were subsequently structured in a hierarchical and coherent manner using TISM. TISM, as described by Obi et al. (2023), is a robust methodology used to simplify intricate and poorly articulated models of various systems into clear and unequivocal representations. Its primary objective is to uncover relationships among the considered elements, thereby improving comprehension of the system's framework. TISM is primarily designed as a collaborative learning process that relies on the collective judgment of the group for decision-making. The approach is interpretative, as it depends on the group's judgment to determine whether and how variables are interconnected, while also being structural, as it derives an overall structure from a complex array of variables based on these relationships (Obi *et al.,* 2023). TISM consists of several systematic stages, beginning with the creation of a structural and reachability matrix, followed by partitioning levels to form a directed graph, and concluding with an examination of structural self-interaction matrices (SSIM) for classification and categorization purposes. Through SSIM analysis, factors are classified into distinct groups based on their levels of influence, which can be separate, interdependent, or self-regulating. TISM has been successfully applied in various research studies to explore relationships among these factors and visually represent their hierarchical structures.

In this research, the TISM methodology was pivotal in establishing a hierarchical structure of relationships among validated drivers and barriers, visually representing them based on expert assessments. Expert opinions underwent content analysis before being integrated into the TISM process. This approach led to the generation of a reachability matrix, TISM diagram, and driver power-dependence matrix for both influential drivers and barriers. The following 9 steps regime designed by Sushil (2012) was utilized:

1. Drivers and barriers were identified and defined through a comprehensive literature review, which was then validated by local experts.
2. Contextual relationships for the identified drivers and barriers were established, resulting in the creation of the Structural Self-Interaction Matrix (SSIM) (refer to Tables 5 & 6). The input from 22 FM organizations was solicited to identify these relationships (see Tables 9 & 10).
3. The Initial Reachability Matrix (IRM) was developed from the SSIM by converting linguistic symbols into a binary system (see Tables 7 & 8).
4. The Final Reachability Matrix (FRM) was derived from the IRM by incorporating transitive links into the model (refer to Tables 9 & 10).
5. Each FRM was partitioned into different levels based on the relationships between driving variables (reachability) and dependent variables (antecedent) (see Tables 7 & 8).
6. Level 1 was assigned to drivers/barriers with identical reachability set (row values) and intersection set (common values between reachability set and antecedent set). Subsequently, variables in the preceding level were removed for the subsequent level partitioning until all variables under study were assigned a level. However, it's important to note that the iteration level does not necessarily guarantee the same level for variables.
7. Digraphs were constructed by identifying various levels of elements once transitivity was confirmed.
8. The resulting digraph was transformed into a model by elucidating the relationships between variable nodes. In Figures 3 and 4, black arrows represent relationships between different levels, while blue arrows denote relationships within the same level.
9. To ensure consistency, the model underwent rigorous analysis by experts. The resulting model from the relationship statement provides a structured hierarchy of drivers and barriers for Climate Change Management Systems (CCMS) in the Identified Issues System Interface (IISI).

The TISM analysis provided valuable insights into the interrelationships among contextual factors and the diverse levels of influence observed between drivers and barriers. These findings were instrumental in constructing models that highlight influential drivers and barriers affecting the adoption of AI in addressing climate change challenges outlined in this study.

The TISM analysis provided valuable insights into the interrelationships among contextual factors and the diverse levels of influence observed between drivers and barriers. These findings were instrumental in constructing models that highlight influential drivers and barriers affecting the adoption of AI in addressing climate change challenges outlined in this study.

TISM is selected over alternative methods such as factor analysis, Analytic Hierarchy Process (AHP), and Structural Equation Modeling (SEM) due to its ability to develop a structured model illustrating the complex interrelationships between various factors. TISM extends traditional ISM by incorporating interpretive logic, making it suitable for understanding both hierarchical and contextual relationships. TISM contributes to the research objectives by providing a detailed structural map of the interdependencies among drivers and barriers, which is essential for comprehending the dynamics of AI adoption in FM. This method facilitates strategic planning by highlighting leverage points where interventions can have the most significant impact.

Integrating the RII and TISM methods provides a robust framework for this research. RII's ability to quantify and rank factors complements TISM's capacity to model complex relationships, offering a comprehensive analysis of AI adoption and use by FM organizations. This methodological choice not only strengthens the validity of the findings but also enhances their practical applicability, ultimately contributing to more informed decision-making in tackling climate change challenges through AI.

**4. Findings**

***4.1 Level of influence of drivers and barriers on adoption of AI***

The analysis of the 2nd part of questionnaire data from FM organizations, utilizing the Relative Importance Index (RII), is presented in Table 4. Table 4 provides a clear view of the RII values, positive and negative influence of drivers and barriers on AI adoption, overall rankings, and the corresponding influence levels for each driver and barriers.

Table 4. Level of influence of drivers and barriers

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | RII | Influence Level | Rank |
| Drivers | Regulatory Compliance (D12) | 0.865 | H | 1 |
| Long-term Sustainability (D10) | 0.814 | H | 2 |
| Responsible Supply Chain (D15) | 0.793 | M-H | 3 |
| Resilience and Adaptation (D13) | 0.779 | M-H | 4 |
| Market Demand (D11) | 0.776 | M-H | 5 |
| Financial Incentives/Profitability (D6) | 0.745 | M-H | 6 |
| Competitive Advantage and Innovation (D2) | 0.730 | M-H | 7 |
| Risk Management (D16) | 0.714 | M-H | 8 |
| Data Driven Decision Making (D4) | 0.707 | M-H | 9 |
| Lifecycle Cost Savings (D9) | 0.690 | M-H | 10 |
| Enhanced Corporate Reputation as Sustainability Champion (D5) | 0.682 | M-H | 11 |
| Corporate Social Responsibility (D3) | 0.668 | M-H | 12 |
| Resources Efficiency (D14) | 0.647 | M-H | 13 |
| Stakeholder Expectations (D17) | 0.631 | M-H | 14 |
| Investor Pressure (D8) | 0.622 | M-H | 15 |
| Community/End-user Engagement (D1) | 0.574 | M | 16 |
| Health and Well Being of Employees (D7) | 0.535 | M | 17 |
|  | | | | |
| Barriers | Regulatory and Policy Constraints/Barriers (B11) | -0.907 | H | 1 |
| Inadequate Infrastructure: Legacy Systems and Infrastructure (B3) | -0.891 | H | 2 |
| Energy Crisis (B19) | -0.874 | H | 3 |
| Resource Constraints (B13) | -0.86 | H | 4 |
| Lack of Incentives (B6) | -0.846 | H | 5 |
| Lack of Skills and Proper Training (B7) | -0.831 | H | 6 |
| Technical Complexity (B17) | -0.818 | H | 7 |
| Data Privacy, Responsibility and Security Concerns (B2) | -0.802 | H | 8 |
| Lack of Awareness and Education (B5) | -0.787 | M-H | 9 |
| Initial Cost (B4) | -0.765 | M-H | 10 |
| Risk Aversion (B14) | -0.76 | M-H | 11 |
| Market Immaturity (B8) | -0.741 | M-H | 12 |
| Slow/Low Return on Investment (B16) | -0.729 | M-H | 13 |
| Vendor Lock-In (B18) | -0.711 | M-H | 14 |
| Measurement and Reporting Challenges (B10) | -0.703 | M-H | 15 |
| Customer/Client Acceptance (B1) | -0.684 | M-H | 16 |
| Market Uncertainty (B9) | -0.668 | M-H | 17 |
| Short-term Focus (B15) | -0.627 | M-H | 18 |
| Resistance to change (B12) | -0.582 | M | 19 |

As listed in Table 4, the findings reveal that FM organizations prioritized certain drivers in their adoption of AI. Regulatory Compliance (0.865) and Long-term Sustainability (0.814) emerge as highly influential drivers in this regard. This aligns with the results presented by Chui *et al.* (2018) wherein a strong correlation between AI adoption and increased efficiency and cost savings, which can contribute to long-term sustainability against climatic change, was observed. Moreover, as emphasized by Kar *et al.* (2021), there is a growing emphasis on regulatory compliance across various industries and services. This trend underscores the necessity for AI-powered solutions capable of automating compliance tasks, aligning with the primary driver identified from literature and validated by South African FM organizations.

Interestingly, Community/End-user Engagement (0.574) and Health and Well-being of Employees (0.535) are identified by 22 FM organizations as drivers with only medium influence. This suggests that while FM organizations recognize the importance of community engagement and employee well-being, they may not perceive these factors as immediate priorities in their adoption of AI for tackling climate change challenges. This finding echoes the discussions in the literature regarding the evolving role of AI in addressing broader societal and human-centric concerns and the importance of community and end-users’ involvement in successful AI implementation (Moghayedi *et al.,* 2024). Conversely, South African FM organizations face significant barriers to the adoption of AI. Regulatory and Policy Constraints/Barriers (-0.907), Inadequate Infrastructure: Legacy Systems and Infrastructure (-0.891), Energy Crisis (-0.874), Resource Constraints (-0.860), Lack of Incentives (-0.846), Lack of Skills and Proper Training (-0.831), Technical Complexity (-0.818), and Data Privacy, Responsibility, and Security Concerns (-0.802) are identified as the barriers with high negative influence. This corresponds with previous studies highlighting the challenges posed by regulatory frameworks, outdated infrastructure, energy constraints, resource limitations, skill gaps, and data-related concerns in adopting AI technologies (Moghayedi *et al.,* 2023; Malik *et al.*, 2021; Smuha, 2021; Alsheiabni *et al.,* 2019; Kumar *et al.,* 2021). South Africa faces a well-documented energy crisis characterized by power outages (load shedding) and an unstable electricity grid (Moghayedi *et al.,* 2023). This presents a significant challenge for AI adoption in FM as highlighted in the FM organizations response.

It is noteworthy that Resistance to Change (-0.582) emerges as the sole barrier with a medium negative influence. This suggests that while organizational inertia may impede AI adoption to some extent, it is outweighed by the more pressing systemic challenges identified above. This finding resonates with literature emphasizing the need for comprehensive organizational strategies to address various impediments to AI adoption (Smuha, 2021). This placement emphasizes the subtle yet substantial impact that drivers and barriers have on the adoption of AI in addressing climate change challenges. It highlights the critical roles played by these factors and underscores the importance of conducting comprehensive studies, preparing, implementing strategies, policies, and allocating resources by FM organizations before embracing AI technologies. Understanding the extent of influence that drivers and barriers exert on AI adoption offers valuable insights to FM organizations and other built environment entities regarding AI-driven climate change approaches, considering the relative importance assigned to these factors. However, it is crucial to acknowledge that merely understanding the nature of influence does not fully elucidate the levels of interdependence and hierarchical significance among these drivers and barriers. Establishing such nexus is critical in articulating a comprehensive strategy for facilitating the adoption and use of AI to tackle climate change challenges by FM organizations. To bridge this deficiency, a pairwise comparison study was conducted utilizing the TISM methodology. This method enabled the creation of a hierarchical model, offering enhanced understanding of the interrelationships and influential factors among the identified drivers and barriers.

## 4.2 Interpretive Structural Modelling

The last part of the survey was designed to determine the contextual relationships among the validated influential drivers and barriers on adoption of AI for tackling climatic changes challenges by South African FM organizations. The 22 FM organizations utilized AI were requested to articulate the relationships between these 17 drivers and 19 barriers through pairwise evaluations. Participants were specifically directed to define these connections using the phrase "will influence to achieve." These findings formed the groundwork for constructing the Structural Self-Interaction Matrix (SSIM), a vital tool for illustrating the relationships between two factors (drivers or barriers) denoted as "i" and "j." To analyze the final relationships between two factors using the collected responses from FM organizations, the mode function is employed as the sole measure of central tendency for nominal variables.

The SSIM matrix utilized four different symbols to denote these relationships:

V: if factor i influences factor j.

A: if factor j influences factor i.

X: if factor i and j influence each other.

O: if factor i and j are unrelated.

Examples:

*D1 and D2 influence each other: since D1 and D2 mutually influence each other, their relationship is coded as X in the SSIM drivers’ matrix.*

*D1 influences D3, but D3 does not influence D1: as D1 influences D3 without any reciprocal influence, their relationship is coded as V.*

*D1 and D4 do not influence each other: since D1 and D4 are unrelated and have no influence on each other, their relationship is coded as O.*

*D4 influences D2, but D2 does not influence D4: because D4 influences D2 without any reciprocal influence from D2, their relationship is coded as A.*

The process led to the development of the SSIM for both drivers and barriers as shown in Tables 5 and 6.

Table 5. SSIM drivers influencing adoption of AI

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Drivers | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | D11 | D12 | D13 | D14 | D15 | D16 | D17 |
| D1 | X | X | V | O | V | O | O | O | O | V | O | O | V | V | O | O | O |
| D2 |  | X | O | A | V | V | V | O | X | O | V | O | V | V | X | X | V |
| D3 |  |  | X | O | X | O | X | A | O | V | O | A | O | O | O | O | X |
| D4 |  |  |  | X | V | V | V | O | V | V | O | O | V | V | V | V | V |
| D5 |  |  |  |  | X | X | X | V | X | X | A | A | X | X | X | X | V |
| D6 |  |  |  |  |  | X | O | A | X | X | A | A | X | A | A | O | A |
| D7 |  |  |  |  |  |  | X | O | V | X | O | A | X | O | O | A | A |
| D8 |  |  |  |  |  |  |  | X | V | V | O | O | O | O | O | O | X |
| D9 |  |  |  |  |  |  |  |  | X | X | A | A | A | A | A | A | X |
| D10 |  |  |  |  |  |  |  |  |  | X | A | A | X | X | X | X | A |
| D11 |  |  |  |  |  |  |  |  |  |  | X | A | O | O | O | O | O |
| D12 |  |  |  |  |  |  |  |  |  |  |  | X | V | O | O | V | V |
| D13 |  |  |  |  |  |  |  |  |  |  |  |  | X | X | X | X | X |
| D14 |  |  |  |  |  |  |  |  |  |  |  |  |  | X | A | O | A |
| D15 |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X | A | A |
| D16 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X | A |
| D17 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X |

Table 6. SSIM barriers influencing adoption of AI

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Barriers | B1 | B2 | B3 | B4 | B5 | B6 | B7 | B8 | B9 | B10 | B11 | B12 | B13 | B14 | B15 | B16 | B17 | B18 | B19 |
| B1 | X | A | O | O | A | A | O | A | A | O | A | A | O | A | O | A | A | O | A |
| B2 |  | X | A | O | O | O | A | O | O | A | O | V | O | V | O | O | A | O | A |
| B3 |  |  | X | V | O | A | O | V | V | V | A | V | A | V | O | V | V | V | X |
| B4 |  |  |  | X | A | A | A | A | A | A | A | O | A | V | V | V | A | A | A |
| B5 |  |  |  |  | X | A | A | A | O | O | O | V | O | V | V | O | O | O | O |
| B6 |  |  |  |  |  | X | V | V | O | O | O | V | V | O | O | V | O | V | O |
| B7 |  |  |  |  |  |  | X | V | O | V | O | V | V | V | V | V | V | O | O |
| B8 |  |  |  |  |  |  |  | X | X | O | A | X | A | A | A | A | X | A | O |
| B9 |  |  |  |  |  |  |  |  | X | V | A | V | A | X | V | X | V | A | A |
| B10 |  |  |  |  |  |  |  |  |  | X | A | V | A | V | V | V | V | O | O |
| B11 |  |  |  |  |  |  |  |  |  |  | X | V | V | V | V | V | V | V | V |
| B12 |  |  |  |  |  |  |  |  |  |  |  | X | A | A | A | A | A | A | A |
| B13 |  |  |  |  |  |  |  |  |  |  |  |  | X | V | V | V | V | V | O |
| B14 |  |  |  |  |  |  |  |  |  |  |  |  |  | X | V | V | A | A | A |
| B15 |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X | A | A | A | A |
| B16 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X | A | A | A |
| B17 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X | V | A |
| B18 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X | A |
| B19 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | X |

The symbols in SSIM were then converted into a binary system to create reachability matrices, identifying the driving power drivers and barriers, using the following rules:

* If the cell (i, j) in the SSIM is V, then in the FRM, cell (i, j) is 1 and cell (j, i) is 0.
* If the cell (i, j) in the SSIM is A, then in the FRM, cell (i, j) is 0 and cell (j, i) is 1.
* If the cell (i, j) in the SSIM is X, then in the FRM, both cell (i, j) and cell (j, i) are 1.
* If the cell (i, j) in the SSIM is O, then in the FRM, both cell (i, j) and cell (j, i) are 0.

The process commenced with the formation of the initial binary matrix, which subsequently underwent iterative steps to produce the initial and final reachability matrices, depicted for drivers in Table 7 and for barriers in Table 8.

Table 7.FRM drivers influencing AI adoption

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Drivers | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | D11 | D12 | D13 | D14 | D15 | D16 | D17 | Driving Power |
| D1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 7 |
| D2 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 12 |
| D3 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 5 |
| D4 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 12 |
| D5 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 12 |
| D6 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 5 |
| D7 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 6 |
| D8 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 6 |
| D9 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 6 |
| D10 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 9 |
| D11 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 5 |
| D12 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 11 |
| D13 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 10 |
| D14 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 6 |
| D15 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 8 |
| D16 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 8 |
| D17 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 11 |
| Dependence | 2 | 6 | 7 | 1 | 15 | 13 | 10 | 3 | 15 | 16 | 3 | 1 | 13 | 9 | 8 | 8 | 9 |  |

Table 8.FRM barriers influencing AI adoption

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Barriers | B1 | B2 | B3 | B4 | B5 | B6 | B7 | B8 | B9 | B10 | B11 | B12 | B13 | B14 | B15 | B16 | B17 | B18 | B19 | Driving Power |
| B1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| B2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 4 |
| B3 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 12 |
| B4 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 4 |
| B5 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 6 |
| B6 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 11 |
| B7 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 12 |
| B8 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 7 |
| B9 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 10 |
| B10 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 8 |
| B11 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 15 |
| B12 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 |
| B13 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 12 |
| B14 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 7 |
| B15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 3 |
| B16 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 6 |
| B17 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 10 |
| B18 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 8 |
| B19 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 12 |
| Dependence | 12 | 5 | 5 | 13 | 4 | 1 | 3 | 13 | 9 | 6 | 1 | 17 | 4 | 13 | 13 | 13 | 9 | 7 | 3 |  |

To delineate hierarchy levels, a level was considered attained when the reachability set—comprising a factor and any other factors it influences—aligned with the intersecting set. These level partitions culminated in the formation of the TISM diagrams for drivers and barriers, depicted in Figures 2 and 3. One of the primary strengths of the TISM model is its capacity to highlight the most impactful drivers and barriers that affect the adoption of AI in addressing climate change challenges among South African FM organizations. Typically, the most influential drivers and barriers are located at the foundation of TISM models. As a result, the drivers and barriers positioned at the top of these models depend on those at the base for realization and influence.

The analysis uncovered the influencing strengths and interdependencies related to different drivers and barriers of AI adoption, as depicted in Table 7. The final reachability matrix establishes the most influential drivers and barriers sets (reachability) and the dependence drivers and barriers sets (antecedent). The most influential drivers and barriers sets of AI adoption include the driver/barrier itself and other drivers and barriers that may be influenced by it. It includes every column that is indicated with a "1" in the row associated with the AI adoption being evaluated. Conversely, the dependence drivers and barriers sets (antecedent) include the driver/barriers itself and other drivers/barriers that may impact it. It includes every row that is marked with a "1" in the column related to the AI adoption being studied. Afterwards, the intersection set for each driver or barrier is identified by analyzing their precursor sets and reachability sets. The initial set of influential drivers and barriers is determined by those whose intersection set matches their reachability set. This process of partitioning levels continues until the level of each driver and barrier is established, as shown in Table 9. The first-level influential secures the top position in both TISM models.

Table 9.DriversLevel partitioning of reachability matrix

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Driver** | **Reachability set** | **Antecedent set** | **Intersection** | **Level** |
| Iteration 1 | | | | |
| D5 | 1,2,3,4,5,7,9,10,13,14,16,17 | 1,2,3,4,5,6,7,8,9,10,12,13,14,15,16,17 | 1,2,3,4,5,7,9,10,13,14,16,17 | I |
| D9 | 2,5,6,9,10,13,14,16,17 | 1,2,4,5,6,7,8,9,10,11,12,13,14,15,16,17 | 2,5,6,9,10,13,14,16,17 | I |
| D14 | 2,5,6,9,10,14,16,17 | 1,2,4,5,6,7,8,9,10,12,14,15,16,17 | 2,5,6,9,10,14,16,17 | I |
| Iteration 2 | | | | |
| D1 | 1,3,4,5,9,10,12,13,14,16 | 1,3,5,6,8,10,12,13,17 | 1,3,5,10,12,13 | II |
| D3 | 1,3,5,7,10,12,13,17 | 1,4,5,6,7,8,10,12,13,17 | 1,5,7,10,12,13,17 | II |
| D4 | 4,5,7,9,10,13,14,16,17 | 1,2,4,5,8,11,15,16,17 | 4,5,16,17 | II |
| D6 | 1,2,3,5,6,9,10,14,17 | 6,9,10,11,13,14,15,16,17 | 6,9,10,14,17 | II |
| D7 | 3,5,7,9,10,13,14,17 | 3,4,5,7,8,10,12,13,17 | 3,5,7,10,17 | II |
| D8 | 1,2,3,4,5,7,8,9,10,13,14,16,17 | 8,11,12 | 8 | II |
| D16 | 2,4,5,6,9,10,13,14,16,17 | 1,2,4,5,8,9,10,11,12,13,14,15,16,17 | 2,4,5,9,10,13,14,16,17 | II |
| D17 | 1,2,3,4,5,6,7,9,13,14,16,17 | 2,3,4,5,6,7,8,9,10,11,12,14,16,17 | 2,3,4,5,6,7,9,14,16,17 | II |
| Iteration 3 | | | | |
| D2 | 2,4,5,9,13,14,16,17 | 2,4,5,6,8,9,10,11,14,16,17 | 2,4,5,9,14,16,17 | III |
| D10 | 1,2,3,5,6,7,9,10,13,14,16,17 | 1,3,4,5,6,7,8,9,10,13,14,15,16 | 1,3,5,6,7,9,10,13,14,16 | III |
| D13 | 1,3,5,6,7,9,10,13,16 | 1,2,3,4,5,7,8,9,10,11,13,15,16,17 | 1,3,5,7,9,10,13,16 | III |
| Iteration 4 | | | | |
| D11 | 2,4,6,8,9,11,13,16,17 | 11,12 | 11 | IV |
| Iteration 5 | | | | |
| D12 | 1,3,5,7,8,9,11,12,14,16,17 | 1,3,12,15 | 1,3,12 | V |
| D15 | 4,5,6,9,10,12,13,14,15,16 | 15 | 15 | V |

Table 10.BarriersLevel partitioning of reachability matrix

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Barrier** | **Reachability set** | **Antecedent set** | **Intersection** | **Level** |
| Iteration 1 | | | | |
| B1 | 1,9,12,16 | 1,2,3,4,5,6,8,9,11,12,14,16,17,19 | 1,9,12,16 | I |
| B12 | 1,8,12,14 | 1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19 | 1,8,12,14 | I |
| Iteration 2 | | | | |
| B15 | 3,5,7,8,12,15 | 3,4,5,6,7,8,9,10,11,13,14,15,16,17,18,19 | 3,5,7,8,15 | II |
| Iteration 3 | | | | |
| B4 | 1,3,4,6,7,8,9,10,12,14,15,16,18 | 2,3,4,5,6,7,8,9,10,11,13,14,16,17,18,19 | 3,4,6,7,8,9,10,14,16,18 | III |
| B8 | 1,3,4,5,7,8,9,11,12,15,16,17,18 | 3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19 | 3,4,5,7,8,9,11,12,16,17,18 | III |
| B9 | 1,4,8,9,10,12,14,15,16,17 | 1,2,3,4,7,8,9,10,11,13,14,16,17,18,19 | 1,4,8,9,10,14,16,17 | III |
| B10 | 2,4,8,9,10,12,14,15,16,17 | 2,3,4,5,7,9,10,11,13,17 | 2,4,9,10,17 | III |
| B14 | 1,4,8,9,12,14,15,16 | 2,3,4,5,7,9,10,11,12,13,14,17,18,19 | 4,9,12,14 | III |
| B16 | 1,2,4,6,7,8,9,12,15,16 | 1,2,3,4,6,7,8,9,10,11,13,14,16,17,18,19 | 1,2,4,6,7,8,9,16 | III |
| B18 | 4,8,9,12,14,15,1618 | 3,4,5,6,8,11,13,17,18,19 | 4,8,18 | III |
| Iteration 4 | | | | |
| B2 | 1,2,4,9,10,11,12,14,16,17 | 2,3,5,7,10,11,13,16,17,19 | 2,10,16,17 | IV |
| B5 | 1,2,4,5,7,8,10,12,13,14,15,18 | 5,6,7,8,13,15 | 5,7,8,13,15 | IV |
| B7 | 2,4,5,6,7,8,10,12,13,14,15,16,17 | 4,5,6,7,8,11,13,15,16,17 | 4,5,6,7,8,13,15,16,17 | IV |
| B13 | 2,3,4,5,7,8,9,10,12,13,14,15,16,17,18 | 5,6,7,11,13,19 | 5,7,13 | IV |
| B17 | 1,2,4,7,8,9,10,12,14,15,16,17,18 | 2,3,7,8,9,10,11,13,17,19 | 2,7,8,9,10,17 | IV |
| Iteration 5 | | | | |
| B3 | 1,2,3,4,8,9,10,12,14,15,16,17,18,19 | 3,4,6,19 | 3,4,19 | V |
| B6 | 1,3,4,5,6,7,8,12,13,15,16,18 | 4,6,11,16 | 4,6,16 | V |
| B11 | 1,2,4,6,7,8,9,10,11,12,13,14,15,16,17,18,19 | 2,8,11 | 2,8,11 | V |
| B19 | 1,2,3,4,8,9,12,13,14,15,16,17,18,19 | 3,11,19 | 3,19 | V |

Ultimately, the TISM digraphs were developed using the reachability matrices (Table 9) and the partition levels established (Table 10) for both drivers and barriers (Figure 2 & 3). The TISM diagram depicting drivers and barriers, as depicted in Figures 2 and 3, underscores the pivotal role and influence of the Regulatory factor. Regulatory and policy are observed to serve as both one of the most influencing drivers (positively) and barriers (negatively) within adoption of AI for tackling the climatic change challenges.

A screenshot of a computer screen

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Figure 2. AI driver framework

In Level 5 of the framework for AI adoption in addressing challenges related to climatic changes, Regulatory Compliance (D12) and Responsible Supply Chain (D15) emerge as the most influential drivers. While there is no direct relationship between these two drivers in Level 5, both significantly influence Market Demand (D11) in Level 4, which subsequently affects drivers in Level 3: Competitive Advantage and Innovation (D2), Long-term Sustainability (D10), and Resilience and Adaptation (D13). Furthermore, the presence of discernible relationships among these three drivers at the same levels is depicted by blue arrows, signifying bilateral influence. These connections underscore the significant role of FM organizational policies in leveraging innovations, promoting long-term sustainability, and fostering resilience and adaptation in the adoption of AI to address climatic changes.

The drivers in Levels 5, 4, and 3 with high influencing power play a pivotal role in shaping the eight drivers in Level 2, including Community/End-user Engagement (D1), Corporate Social Responsibility (D3), Data-Driven Decision Making (D4), Financial Incentives/Profitability (D6), Health and Well-being of Employees (D7), Investor Pressure (D8), Risk Management (D16), and Stakeholder Expectations (D17). The confirmed relationships between drivers in Level 2 highlight a close correlation between Community/End-user Engagement (D1), Corporate Social Responsibility (D3), Health and Well-being of Employees (D7), Investor Pressure (D8), and Stakeholder Expectations (D17), which can be clustered as social drivers influencing AI adoption in FM organizations. Conversely, another close correlation exists between Data-Driven Decision Making (D4), Financial Incentives/Profitability (D6), and Risk Management (D16), which were clustered as management drivers.

Although there are no direct relationships between these two clusters of drivers in Level 2, they all directly influence three drivers in Level 1: Enhanced Corporate Reputation as Sustainability Champion (D5), Lifecycle Cost Savings (D9), and Resource Efficiency (D14). While the drivers in Level 1 have the lowest influencing power, as illustrated in Figure 2, there are bilateral influencing relationships among the three drivers in Level 1.

A screenshot of a computer

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Figure 3. AI barriers framework

As depicted in Figure 3, several barriers hold highest influence power over the adoption of AI which located at level 5 of AI barriers framework. These include Inadequate Infrastructure: Legacy Systems and Infrastructure (B3), Lack of Incentives (B6), Regulatory and Policy Constraints/Barriers (B11), and Energy Crisis (B19). These barriers notably impact others positioned above them, particularly at Level 4. Among the Level 5 barriers, Regulatory and Policy Constraints/Barriers (B11) emerge with the highest influencing role, as indicated by the internal relationship depicted by the blue arrow.

Within Level 4, barriers affecting the adoption of AI encompass Data Privacy Lack of Awareness and Education (B5), Lack of Skills and Proper Training (B7), Resource Constraints (B13), Technical Complexity (B17), and Responsibility and Security Concerns (B2). Primarily, these barriers are associated with a lack of knowledge, skills, and awareness, which contribute to the complexity of AI and, consequently, jeopardize responsibility and security, as demonstrated by the internal relationships between these barriers.

The barriers at Level 4 directly influence seven barriers at Level 3, including Market Uncertainty (B9), Market Immaturity (B8), Vendor Lock-In (B18), Initial Cost (B4), Slow/Low Return on Investment (B16), Risk Aversion (B14), and Measurement and Reporting Challenges (B10). While there are bilateral influences between five of the barriers at this level, Vendor Lock-In (B18) in AI in South Africa affects the initial cost of AI adoption, as well as Slow/Low Return on Investment (B16) and Measurement and Reporting Challenges (B10), influencing Risk Aversion (B14), but not vice versa.

The barriers to AI adoption at Levels 5, 4, and 3 influence FM organizations in South Africa to prioritize short-term goals, thereby fostering a Short-term Focus (B15), as depicted in Level 2. Ultimately, this short-term focus impacts two social barriers to the adoption of AI for addressing climatic changes, namely: Customer/Client Acceptance (B1); and Resistance to Change (B12).

The analysis was further expanded using the Cross-Impact Matrix Multiplication Applied to Classification (MICMAC) method. This method categorizes factors (drivers/barriers) into specific groups based on their dependency characteristics. Influencing power of a factor denotes the total number of factors, including itself, that it can impact or contribute to. On the other hand, dependence refers to the total number of factors that can contribute to achieving a specific factor. Drawing from established research methodologies, the autonomous cluster encompasses factors with minimal influencing and dependence powers. Dependent clusters consist of variables with low influencing power yet high dependence. Independent clusters involve variables with substantial influencing power but low dependence, while linkage clusters feature variables with high levels of both influencing and dependence powers. The final reachability matrix was transformed to create the MICMAC diagram. This transformation included aggregating scores across each respective row to ascertain a factor's influence and across each respective column to define its dependency. The results of the MIC-MAC analysis for drivers and barriers are presented in Figure 4 and 5.

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Description automatically generated

Figure 4. Classification of drivers of AI based on a MICMAC analysis

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Figure 5. Classification of barriers of adoption of AI based on a *MICMAC analysis*

The drivers and barriers influencing the adoption of AI for addressing climatic changes have been organized into four quadrants based on their levels of influencing power and dependence, as depicted in Figures 4 and 5. In this framework, the x-coordinate denotes the level of dependence power, whereas the y-coordinate indicates the degree of influencing power.

The first quadrant, known as the "autonomous cluster," includes factors characterized by low influencing power and low dependence. These factors generally function independently within the system and have minimal connections to other elements. As illustrated in Figures 4 and 5, no drivers or barriers fall within this quadrant, suggesting that none of the identified AI drivers and barriers in this study function as disconnected entities from others.

The second quadrant, known as the "dependence cluster," includes drivers and barriers with weak influencing power but strong dependence on other factors. In Figure 4, drivers such as Competitive Advantage and Innovation (D2), Corporate Social Responsibility (D3), Health and Well-being of Employees (D7), and Resource Efficiency (D14) are situated here, highlighting their reliance on other AI drivers. This positioning highlights the reliance of these drivers, particularly social drivers such as innovation utilization and resource efficiency, on other AI drivers predominantly in the fourth quadrant. Similarly, in Figure 5, barriers like Customer/Client Acceptance (B1), Resistance to Change (B12), Risk Aversion (B14), Short-term Focus (B15), and Vendor Lock-In (B18) are dependent and could potentially be mitigated by addressing independent barriers.

The third quadrant, referred to as the "linkage cluster," comprises factors with both strong influencing power and strong dependence. These interconnected factors imply that changes in one element will affect others. Drivers such as Community/End-user Engagement (D1), Data-Driven Decision Making (D4), and barriers including Lack of Skills and Proper Training (B7) and Technical Complexity (B17) are located in this quadrant, indicating their significant impact on other drivers and barriers. Due to their inherent instability, these drivers and barriers are likely to trigger a cascade effect, impacting other aspects within the system and consequently influencing the overall adoption of AI in addressing climate change challenges.

The fourth quadrant, termed the "independent cluster," comprises factors with strong influencing power but weak dependence. Here, drivers such as Investor Pressure (D8), Market Demand (D11), and Regulatory Compliance (D12) are situated. This observation emphasizes the crucial role and significant impact of investors, market demand, supply chain, and regulatory frameworks in driving the adoption of AI and shaping it as a mechanism for addressing climate change. Barriers such as Lack of Awareness and Education (B5) and Inadequate Infrastructure (B3) are also found in this quadrant. These independent barriers significantly influence others and addressing them could facilitate the adoption of AI for addressing climate change challenges.

Finally, to summarize the study's findings, the hierarchy and influence levels of the drivers and barriers affecting the adoption of AI for tackling climate change are illustrated in Figure 6.

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Figure 6. Influencing Levels of Drivers and Barriers on the Adoption of AI in FM Organizations and Tackling Climate Change

# 5. Discussion

The study aimed to investigate the perspectives of Facilities Management (FM) organizations in South Africa regarding the adoption of Artificial Intelligence (AI) for addressing climate change challenges. Specifically, it sought to identify the key drivers and barriers influencing AI adoption in this context, assess their respective levels of influence, and analyze their interrelationships to develop comprehensive frameworks for addressing climatic changes. The findings of the study reveal significant and varied influence of drivers and barriers on the adoption of AI by FM organizations. Across the spectrum, these factors exert a mixed influence ranging from medium to high. Notably, the study highlights the prevalence of barriers, outnumbering drivers in both quantity and intensity. With 17 drivers (comprising 2 with high influence, 13 with medium to high influence, and 2 with medium influence) compared to 19 barriers (including 8 with high influence, 10 with medium to high influence, and 1 with medium influence), it becomes apparent that barriers pose a formidable challenge to AI adoption in the FM sector. This observation is further underscored by the overall influence scores, with drivers collectively scoring 0.704 compared to barriers scoring -0.768, indicating a predominance of inhibitory factors hampering the adoption of AI.

The findings of this study provide valuable insights into the drivers and barriers influencing the adoption of AI for addressing challenges related to climatic changes within FM organizations. Through a comprehensive analysis, the study elucidates the complex dynamics shaping AI adoption and highlights the interconnectedness of various factors within the adoption frameworks for influencing drivers and barriers. At the forefront of AI adoption for addressing climatic changes are drivers such as Regulatory Compliance and Long-term Sustainability, which emerge as highly influential factors. These findings resonate with existing literature, which emphasizes the importance of regulatory frameworks and sustainability initiatives in driving technological innovation, particularly in response to environmental challenges (Smuha, 2021; Almeida *et al.*, 2022). The prioritization of these drivers underscores the imperative for FM organizations to align with regulatory requirements and adopt sustainable practices, leveraging AI technologies to enhance efficiency and mitigate climate-related risks. Interestingly, while drivers such as Community/End-user Engagement and Health and Well-being of Employees are recognized as important, they are perceived with only medium influence. This finding echoes discussions in the literature regarding the evolving role of AI in addressing broader societal concerns and the need for human-centric approaches (Li and Lu, 2021; Klein *et al.*, 2020; Herath and Mittal, 2022; Nazareno and Schiff, 2021; Braganza *et al.,* 2021; Budhwar *et al.,* 2022; Malik *et al.*, 2021; Moghayedi *et al.*, 2024). It suggests a potential gap between organizational priorities and the broader societal impacts of AI adoption, highlighting the need for organizations to consider the social implications of their technological investments.

On the other hand, significant barriers hinder the adoption of AI for addressing climatic changes, including Inadequate Infrastructure, Lack of Incentives, Regulatory and Policy Constraints, and Energy Crisis. These barriers underscore the multifaceted challenges faced by FM organizations in embracing AI technologies in South Africa, ranging from infrastructural limitations to regulatory complexities and resource constraints. These findings align with previous research highlighting the challenges posed by regulatory frameworks, outdated infrastructure, and energy crises in adopting AI technologies (Moghayedi *et al.,* 2023). Of particular concern is the prominence of Regulatory and Policy Constraints as a barrier with the highest influencing role. This emphasizes the need for supportive regulatory environments that facilitate innovation and incentivize sustainable practices. Without clear regulatory frameworks and policies, FM organizations may face uncertainties and obstacles in implementing AI solutions to address climate change challenges.

The study delves into an in-depth analysis of the interrelationships among drivers and barriers, culminating in the development of two pivotal frameworks: the AI drivers’ framework and the AI barriers framework.

Through meticulous analysis, a hierarchical framework emerges, offering a structured comprehension of the intricate dynamics that influence AI adoption. These frameworks unveil clusters of drivers and barriers with varying degrees of influence and dependence, shedding light on the interconnectedness of drivers and barriers throughout the adoption process. For instance, social drivers such as Community/End-user Engagement exhibit a close association with management drivers like Data-Driven Decision Making, emphasizing the pivotal role of stakeholder engagement in formulating effective AI adoption strategies. This interconnectedness underscores the significance of a holistic approach in navigating the complexities of AI implementation within FM organizations. These frameworks serve as invaluable guidelines and roadmaps for FM organizations aiming to leverage AI in addressing climatic changes.

# 6. Implications

The findings of this study have significant implications for both theory and practice. It offers valuable insights into the dynamics of AI adoption for climate change mitigation in the FM sector, serving as a reference for policymakers, practitioners/managers, and researchers. These insights can help promote the effective use of AI technologies to address climate change impacts, thereby enhancing the sustainability and resilience of the built environment.

***6.1 Theoretical Implications***

The findings of this study have significant theoretical implications, advancing the understanding of the drivers and barriers influencing AI adoption in the context of climate change mitigation efforts. This research emphasizes the importance of a holistic approach that integrates organizational priorities with broader environmental and societal impacts. Through integration of RII and TISM, the study provides a comprehensive analysis of the complex interdependencies and hierarchical significance of various factors. This methodological approach enriches the existing literature by offering a structured framework to analyze the adoption of AI technologies for tackling climate change challenges, which can be applied to other contexts within the built environment. Moreover, the study bridges a significant gap by focusing on South Africa, a developing nation in the Global South facing substantial climate challenges, thus adding a crucial perspective to the global discourse on AI adoption and climate resilience.

***6.2 Practical/Managerial Implications***

For practitioners and managers in the FM sector, this study offers valuable insights into the critical drivers and barriers to AI adoption. Regulatory compliance, a responsible supply chain, providing adequate training, and fostering stakeholder engagement are identified as pivotal drivers, emphasizing the need for organizations to align their AI strategies with regulatory frameworks and ethical supply chain practices. On the other hand, significant barriers such as policy constraints and energy crises highlight areas where intervention is required to facilitate AI adoption. By understanding the nuanced and interconnected nature of the drivers and barriers, practitioners and managers can design effective AI adoption strategies that align with both organizational goals and societal and environmental needs. Policymakers can use these findings to develop supportive regulatory frameworks that create an enabling environment for AI adoption. This includes providing incentives and resources to overcome significant barriers such as policy constraints and energy crises.

# 7. Conclusion

The findings of this study provide valuable insights into the adoption of AI by FM organizations for addressing climate change challenges. Through a comprehensive analysis of drivers and barriers, the study sheds light on the multifaceted dynamics influencing AI adoption within the FM sector in South Africa. The study for the first time reveals a diverse range of drivers and barriers influencing AI adoption, with varying levels of influence for tackling climate change challenges. While drivers such as Regulatory Compliance and Long-term Sustainability demonstrate significant positive influence, barriers such as Regulatory and Policy Constraints and Inadequate Infrastructure pose substantial challenges. These findings underscore the complex nature of AI adoption within the FM sector, requiring careful consideration of both enabling factors and hindrances.

Despite the presence of enabling drivers, barriers outnumber and exert a stronger overall influence on AI adoption. This imbalance highlights the critical need for FM organizations to address inhibitory factors such as regulatory constraints, infrastructural limitations, and skill gaps to facilitate effective adoption of AI technologies. Failure to overcome these barriers may impede progress towards leveraging AI for climate change mitigation efforts. The study identifies interconnected relationships between drivers and barriers, highlighting the need for a holistic approach to AI adoption. By developing frameworks that capture these interdependencies, FM organizations can better navigate the complexities of AI adoption and develop strategies that address both enabling factors and hindrances. These frameworks serve as valuable tools for guiding decision-making and resource allocation towards sustainable AI adoption practices.

The findings of this study underscore the importance of addressing barriers and leveraging drivers to facilitate the effective adoption of AI technologies for addressing climate change challenges within the FM sector. By embracing a holistic approach and implementing targeted interventions, FM organizations can unlock the transformative potential of AI to drive sustainability and resilience in the face of climate change. Based on the findings of this study, several recommendations emerge to facilitate the effective adoption of AI by FM organizations for addressing climate change challenges. Policymakers should focus on creating supportive regulatory frameworks that incentivize AI adoption while addressing legal and compliance barriers. Streamlining regulations and promoting collaboration between public and private sectors can create an enabling environment for innovation and experimentation. FM organizations should prioritize investments in infrastructure development and workforce training to overcome technical and skill-related barriers. Initiatives aimed at enhancing digital literacy and fostering a culture of innovation can empower employees to embrace AI technologies effectively. Collaboration between stakeholders, including government agencies, industry partners, and research institutions, is essential for driving collective action towards AI adoption. By fostering partnerships and knowledge-sharing networks, FM organizations can leverage collective expertise and resources to overcome barriers and accelerate progress towards climate resilience. Adopting a systematic approach to monitoring and evaluating AI adoption initiatives is crucial for identifying challenges and opportunities in real-time. Regular assessments of progress and impact can inform adaptive management strategies and enable organizations to course correct as needed.

While this study specifically examined South African FM organizations, its implications extend beyond this context to encompass a wider array of built environment organizations grappling with climate change challenges. By shedding light on the drivers and barriers influencing the adoption of innovative technologies like AI, this research contributes significantly to the discourse on sustainability. The insights gleaned from this study can be extrapolated to inform decision-making processes in similar organizations across the Global South, aiding in tackling climatic changes in organization level. Furthermore, the findings serve as a valuable foundation for future research endeavors aimed at addressing the unique needs and contexts of diverse regions within the Global South.

Despite the comprehensive nature of this study, it is important to acknowledge certain limitations. The findings predominantly rely on a limited sample size of registered FM organizations in South Africa, particularly those that have already integrated AI technologies. Consequently, the generalizability of the study's conclusions is confined to the FM sector within South Africa may not directly extrapolate to other sectors of the built environment. Future research efforts should prioritize larger sample sizes encompassing diverse regions within the Global South and various sectors of the built environment. The generalizability of findings will be enhanced, and understanding of AI adoption dynamics and its implications for addressing climate change challenges effectively will be deepened.

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