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A comprehensive analysis of the implications of artificial intelligence adoption on employee social well-being in South African facility management organizations

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Abstract

Purpose – The purpose of this study is to explore the increased uptake of Artificial Intelligence (AI) technology by Facility Management (FM) organizations for enhanced operational efficiency and competitive advantage. While AI adoption in FM has been widely reported, limited attempts have been made to assess its impact on the social well-being of FM employees. To contribute towards addressing this gap, this study established the essential employee social well-being factors mostly impacted by the adoption of AI in South African FM organizations.

Design/methodology/approach – A four-stage design comprising a comprehensive review of literature, expert interviews, questionnaire census and focus group discussion sessions was used to elicit data from a sample of participants drawn from 22 South African FM organizations. The data was analyzed using a combination of content analysis, relative importance index and interpretative structural modeling for various data sets toward achieving the study's objectives.

Findings – Sixteen employee social well-being factors, classified under job satisfaction, social relationship and knowledge development categories, respectively, were identified as being impacted by AI adoption in FM organizations. Furthermore, it was established that job security, job autonomy and professional status, which belong to the job satisfaction social well-being factor category, were deemed by FM employees as being mostly impacted by AI adoption.

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Practical implications – The enhanced understanding of the impact of AI adoption on FM employees' social well-being factors will contribute to the development of a collaborative intelligence framework for managing AI adoption in FM organizations toward engendering optimal AI–FM employee relationships for improved productivity.

Originality/value – Besides being one of the foremost studies to investigate the impact of AI adoption on FM employees' social well-being, this study introduces a hierarchical framework of understanding employee social well-being factors based on multi-stakeholder perspectives.

Keywords South Africa, Employee, Artificial intelligence

Paper type Research paper

1. Introduction

The fourth industrial revolution has led to the emergence of a variety of disruptive technologies (Ramakrishna *et al.*, 2020). Various reasons, ranging from improved digitization, data gathering and processing, process efficiency and effectiveness, sustainable production and consumption, productivity and profitability, among others, remain responsible for the increasing uptake of these technologies (Hopster, 2021). True to their potential, these technologies have contributed to societal transformation (Hopster, 2021) and business model innovation in different sectors, changing the way business is conducted. The architecture, engineering, construction and operation (AECO) sector is not left out of such business model transformation resulting from the adoption of these technologies. Despite lagging other sectors like manufacturing, retail and healthcare in this regard, the AECO sector has recorded considerable progress regarding technology adoption. However, the adoption of these technologies within its FM subsector is regarded as nascent.

As a profession, FM encompasses the sum of managerial practices relating to the use, operation, development, maintenance and improvement of physical assets (Nielsen *et al.*, 2016). Also, Pedral Sampaio *et al.* (2023) highlight the profession's multidisciplinary nature and its contributions toward meeting the strategic and functional needs of the end-user. FM's contribution to societal well-being and quality of life, as well as organizational efficiency and productivity, are further elucidated in the BS EN ISO 41001:2018. As a result of its growing importance, the relevance of FM expertise and knowledge for tackling challenges such as climate adaptation, energy and resource efficiency has been reported (Nielsen *et al.*, 2016; Opoku and Lee, 2022). Furthermore, scholars have compiled examples of digital technology deployment in FM practice, highlighting the drivers and barriers influencing successful adoption (Konanahalli *et al.*, 2020; Araszkiewicz, 2017). Also, the benefits derived from increased adoption of digital technologies for enhancing FM practice have been reported (Pedral Sampaio *et al.*, 2023; Hübner *et al.*, 2022).

The positive impact of the adoption of these digital technologies in FM, especially as it concerns innovative work practices, as well as effective and efficient maintenance regimes resonates (Arsiwala *et al.*, 2023; Gunasekara *et al.*, 2022; Baskaran *et al.*, 2020). However, few studies have articulated its impact, on the social well-being of FM employees (Reinke and Ohly, 2021; Atkin and Bildsten, 2017; Adama and Michell, 2018). The limited scope of comprehensive research and reporting on the effects of digital technology adoption on FM workers is among the main reasons for the lower utilization of such technologies in the FM sector compared to other sectors and industries (Troje, 2023). Adama and Michell (2018) highlight the seeming prioritization of operational efficiency and effectiveness over employee health and well-being within FM organizations. Considering the impact of poor levels of FM employee health and well-being on the overall productivity and performance of the FM organization (Shin and Konrad, 2017), the determination and subsequent

management of the implications of digital technologies adoption on the FM employee's social well-being, particularly as it relates to social constructs, has become imperative.

AI has been identified as a digital technology that has demonstrated considerable utility in advancing FM practice (Atkin and Bildsten, 2017; Marzouk and Zaher, 2020; Vaiste, 2020). The adoption of AI in the FM sector has gained traction in recent times, particularly with the advent of intelligent and smart buildings that can anticipate end-users changing needs and engage in real-time decision-making to meet such needs (Windapo and Moghayedi, 2020). Also, such integration has contributed to the emergence of innovative FM regimes like cognitive FM (Xu *et al.*, 2019). The tendency for AI-related capabilities such as process automation, predictive maintenance and facility cleaning needs, space planning and optimization, energy monitoring, measurement and verification, and demand management (Himeur *et al.*, 2023; Moghayedi *et al.*, 2023; Chew *et al.*, 2020), to engender technological dis-enhancement of FM employees while still undermining their social well-being has been reported. Adama and Michell (2018) describe FM employees as making salient contributions to the quality of FM service delivery. Accordingly, their social well-being should be prioritized. However, an overt focus on AI capabilities may undermine social well-being levels among these FM employees. The need to develop frameworks for facilitating effective AI–employee collaboration, leveraging a socio-technical systems theoretical perspective, has been highlighted (Chowdhury *et al.*, 2022; Yu *et al.*, 2023). These frameworks need to be predicated on a comprehensive understanding of AI's impact (the technical subsystem) on prevailing social constructs within the work environment (including employee social well-being) as both components are mutually beneficial to achieving improved organizational performance (Chowdhury *et al.*, 2022).

However, a paucity of studies seeking to study the (potential) implications of AI adoption on FM employees' social well-being within the South African FM space has been observed. Noticeably, studies seeking to explore similar phenomena within South Africa (Adama and Michell, 2018) have focused on technological innovations as a collective and relied on a mono-method methodological choice for data elicitation. However, the current study focuses solely on AI and uses a mixed-method methodological choice for data elicitation.

As its contribution to the extant discourse regarding the phenomenon being studied, this study seeks to answer the following research questions:

RQ1. How does AI adoption impact on the social well-being of FM employees?

RQ2. What are the most critical aspects of FM employees' social well-being impacted by the adoption of AI?

It is expected that the findings from this study will offer new insights to FM practitioners in South Africa and the rest of sub-Saharan Africa on how to engender optimal levels of AI–employee collaboration and by extension, improve FM organizational performance.

2. Literature review

2.1 Artificial intelligence and facility management

The role of the facilities management (FM) profession in providing an enabling environment for business productivity and individual health and well-being, as well as sustainable futures, has been established (Ikuabe *et al.*, 2023; Opoku and Lee, 2022). As a result, the profession has gained global acceptance across various economic sectors ranging from healthcare, education and logistics to manufacturing, among others, providing support services that enable clients to achieve their core offerings. Accordingly, global FM peaked at

$1.239.99bn in 2021, with an estimated 5.7% annual growth rate projected for the coming years (Pedral Sampaio *et al.*, 2023).

The dynamic business environment within which organizations operate necessitates continuous improvement in FM services being provided to these organizations to enable them to gain a competitive advantage (Araszkiewicz, 2017). Therefore, optimizing FM service delivery in a cost-effective and efficient manner remains critical (Araszkiewicz, 2017). The quest for FM-related innovations, which are aimed toward the adoption of a longer-term focus on sustainable maintenance and operation practices, is predicated on this (Opoku and Lee, 2022). Accordingly, several studies have focused on the use of AI in the FM sector to sustain such innovations. Obviously, this is due to the multifarious contributions of AI toward enhancing the performance of other digital technologies such as Internet of Things (IoT) and blockchain.

Herweijer (2017) and Marinchak *et al.* (2018) describe AI as involving computer algorithms used for actualizing tasks which would usually require functions associated with considerable human cognition and intelligence Also, AI's ability to enable the mining of significant amounts of data for the purposes of effective and real-time decision-making has been reported (Choi and Shin, 2019). Chowdhury *et al.* (2022) highlight AI's contribution to business model innovation and a data-centric and digital-oriented organizational culture in the workplace. According to Statista (2023), the AI market is expected to attain the $2tn mark by 2030 from its current $207m, hence highlighting its growing relevance and acceptance, globally.

The adoption of AI in FM is well-documented. Pedral Sampaio *et al.* (2023) described the use of AI for effective and efficient FM information management in a hospital facility. Cao *et al.* (2015) proposed an AI-based model for automatically analyzing and prioritizing future work requests relying on safety, energy consumption impact and occupant satisfaction indicators for a university's facilities. Furthermore, Marzouk and Zaher (2020) developed an AI-led methodology for classifying and localizing mechanical, electrical and plumbing (MEP) systems within a facility based on object and material recognition, damage detection, progress monitoring and location identification capabilities of AI. Lok *et al.* (2022) developed and validated an AI-based FM outsourcing relationship system for the delineation of extant client–supplier outsourcing relationships into categories based on a series of rules. Chen *et al.* (2022) developed an integrative framework consisting of robotics, AI and BIM for bridging physical defects using digital representations. The significance of AI in the management of smart buildings and facilities has been emphasized (Bechina and Arntzen, 2022; Zhang *et al.*, 2022; Chew *et al.*, 2020). Xu *et al.* (2019) reviewed AI's role in enabling cognitive FM. Furthermore, Arsiwala *et al.* (2023) demonstrated AI's utility in enabling predictive monitoring of CO_2 emissions from existing buildings, leveraging IoT and digital twin. Likewise, Moghayedi *et al.* (2023) highlighted the pivotal role of AI in fostering environmental sustainability, promoting circular economy practices and achieving net-zero carbon futures.

From the foregoing, it can be deciphered that the introduction of AI into the workplace has led to individual, organizational and employment-related outcomes. Its impact has been observed across facets like job categories, number of working hours, employer-employee relationships and remuneration models (Yu *et al.*, 2023). Accordingly, increased AI adoption in the workplace has deepened apprehension levels among employees regarding job security and social well-being. This is especially the case as AI's potential to displace more than 75 million jobs while creating 133 million jobs by 2023 has been elucidated (WEF, 2018). Heightened apprehension among employees has hindered the development of collaborative intelligence capabilities in organizations resulting from mainstreaming AI-led practices into

hitherto human-driven organizational processes and solutions (Yu *et al.*, 2023; Chowdhury *et al.*, 2022). The tendency of this challenge to negate AI's contribution to organizational performance remains apparent (Yu *et al.*, 2023; Troje, 2023). This is particularly the case in FM where a variety of hitherto human-driven tasks are now being implemented by AI. Therefore, improving collaboration between AI and FM employees remains imperative. Obviously, the development of capabilities for enabling such collaboration can only commence with the determination of the facets of the employee-related social constructs that are mostly (likely to be) affected by AI adoption in the FM organization. However, elucidating relevant facets associated with AI-employee collaboration remains under-researched (Chowdhury *et al.*, 2022; Yu *et al.*, 2023). This was further corroborated by Adama and Michell (2018) as it pertains to technological innovations and employees' social well-being within South Africa's FM context. This study intends to address this gap.

2.2 Employee social well-being factors and artificial intelligence adoption

Measuring the well-being of workers is a multidimensional task that requires consideration of various constructs and factors. According to the World Health Organization (WHO, 2019), the well-being of workers includes subjective or psychological measures of an individual's well-being, involving an assessment of both quality of life and employment. This is usually determined through three main constructs: social relationships (Stone *et al.*, 2013), job satisfaction (Attar and Sweis, 2010) and knowledge development (Dempsey *et al.*, 2011). These are three basic social constructs that underpin employee social well-being and affect employee productivity and commitment to value addition in organizations.

2.2.1 Social relationship. Social relationships in the workplace encompass the interactions, connections and associations that employees have within a social context, including relationships with colleagues, supervisors and the broader organizational community (Stone *et al.*, 2013). Positive social relationships contribute to a supportive work environment, fostering collaboration, communication and a sense of belonging. Such positive relationships contribute to emotional well-being by providing a sense of belonging and support, leading to higher emotional satisfaction. Furthermore, social relationships play a crucial role in job satisfaction, influencing the overall work environment and, consequently, employee well-being. Supportive social networks act as a buffer against workplace stress, enabling employees to cope more effectively with stressors and enhancing their overall well-being (Abendroth and Schwarz, 2023). Healthy social relationships also foster collaboration and teamwork, positively impacting productivity and contributing to the overall well-being of employees. Similarly, workplace engagement, a critical aspect of well-being, is closely linked to social relationships, with engaged employees experiencing higher levels of overall well-being (Ozyilmaz, 2020).

The literature underscores five factors within the social relationships construct, namely, alienation (Grimshaw, 2007; Barrett and Baldry, 2009), social isolation (Connor *et al.*, 2018), work and home-life balance (O'Driscoll *et al.*, 2009), social network (Golden *et al.*, 2008; Lam and Lau, 2012) and overwork (O'Driscoll *et al.*, 2009; Kossek *et al.*, 2009; Pfeffer, 2009):

- Alienation: Alienation in the workplace refers to the sense of detachment or estrangement that employees may experience. High levels of alienation can negatively impact well-being by creating feelings of isolation and disconnection from colleagues and the organization.
- Social isolation: Social isolation occurs when individuals lack meaningful connections and interactions with their peers and superiors. This variable is closely

linked to feelings of loneliness and can adversely affect the emotional well-being of workers.

- Work and home-life balance: Achieving a balance between work and personal life is a crucial aspect of social well-being. The ability to manage responsibilities both at work and home contributes significantly to overall well-being.
- Social network: The strength and diversity of social networks within the workplace play a vital role in employee well-being. A supportive social network fosters collaboration, communication and a positive work environment.
- Overwork: Overworking, often a result of excessive workload and prolonged working hours, can strain social relationships. It is associated with higher stress levels and reduced well-being among workers.

2.2.2 Job satisfaction. Job satisfaction is a subjective measure of employees' contentment, fulfillment or happiness with their job and the work environment, reflecting how rewarding, meaningful and aligned with the expectations of their work. Influenced by various factors, including the nature of the work, relationships with colleagues and supervisors, compensation and opportunities for professional growth, job satisfaction plays a crucial role in an employee's social well-being (Oduro-Owusu, 2010). Employees who are satisfied with their jobs experience positive emotions, fostering a sense of fulfillment and happiness in their work. Also, such employees tend to be more productive and perform better in their roles, contributing to a positive work environment that impacts job satisfaction and overall well-being. Job satisfaction acts as a buffer that mitigates the negative impact of stressors, contributing to overall social well-being. Interpersonal relationships with colleagues and supervisors are pivotal in shaping overall job satisfaction and well-being. Perceived job security, organizational policies, professional status, remuneration and task requirements further contribute to this multifaceted construct, collectively defining job satisfaction's intricate impact on the comprehensive well-being of employees within the organizational context.

Acknowledging and comprehending these factors within the realm of job satisfaction provides the foundation for exploring their intricate connections to the overall well-being of employees and the impact of AI adoption:

- Autonomy: Autonomy at the workplace refers to employees' degree of independence and control over their work. Higher levels of autonomy contribute positively to job satisfaction as employees feel empowered and engaged in decision-making.
- Interpersonal relationship: The quality of interpersonal relationships with colleagues and supervisors significantly influences job satisfaction. Positive relationships foster a supportive work environment, contributing to overall employee well-being.
- Job security: Perceived job security is a crucial variable in job satisfaction. A sense of stability and confidence in one's employment enhances satisfaction and mitigates stress, positively impacting well-being.
- Organization policy: The policies and practices of an organization, including those related to work-life balance, professional development and diversity, play a pivotal role in shaping job satisfaction and, consequently, overall well-being.
- Professional status: The perceived professional status of employees within the organization influences job satisfaction. Recognition, appreciation and acknowledgment contribute to positive work experience and enhanced well-being.

- Remuneration: Fair and competitive compensation is a fundamental factor in job satisfaction. Adequate remuneration is closely tied to the overall well-being of workers.
- Task requirement: The nature and requirements of job tasks impact job satisfaction. Aligning task requirements with employee skills and interests contributes to enhanced satisfaction and well-being.

The job satisfaction social construct is influenced by job autonomy, interpersonal relationships, remuneration, professional status, organization policy and task requirements (Oduro-Owusu, 2010). According to Dong *et al.* (2021), limited job autonomy can be detrimental to employees' physical and social well-being. Similarly, Yang and Zhao (2018) opined that the level of autonomy experienced by employees is positively related to their psychological well-being. AI adoption by FM organizations has led to the automation of operational processes, thereby making FM employees feel less engaged (Connor *et al.*, 2018). Also, AI adoption can have a negative impact on the remuneration of FM employees, thereby influencing the levels of job satisfaction experienced by the employee (Chowdhury *et al.*, 2022; Marzuki *et al.*, 2012). Obviously, AI adoption by FM organizations will result in a remodeling of roles, thereby pressuring FM employees to upgrade their qualifications and professional status to fit into these roles (Beer and Mulder, 2020). Available evidence has shown that increased AI adoption leads to a reduction in the proportion of interpersonal relationships existing between employees (Drago, 2015). Furthermore, adopting AI in the workplace would engender changes to working practices and organizational policies (Braganza *et al.*, 2021). Atkin and Bildsten (2017) reiterate the potential for AI adoption in the workplace to affect employee task requirements due to the changes in tasks and skillsets.

The literature highlighted above emphasizes the nexus between the seven factors within the construct of job satisfaction.

2.2.3 Knowledge development. Knowledge development encompasses acquiring, enhancing and applying skills, information and expertise over time. This involves activities like on-the-job training, professional development plans and workshops for continuous learning in the workplace. Essential for personal and professional growth, it enables employees to adapt to changing work environments, contribute effectively to their roles and plan for future career advancements. This pursuit of knowledge development within the workplace has emerged as a critical factor influencing the overall well-being of workers. Closely linked to career satisfaction, employees engaging in continuous learning experience higher levels of satisfaction, contributing to their overall well-being. Ongoing knowledge development positively impacts mental well-being, stimulating intellectual curiosity and acquiring new skills, contributing to a sense of purpose and fulfillment. Engaged employees, often interested in knowledge development, enhance job engagement, fostering overall well-being by actively expanding their skills and contributing meaningfully to the workplace. Employees actively involved in knowledge development demonstrate greater adaptability and resilience in the face of change, positively influencing well-being by reducing stress associated with uncertainty. Cultivating a culture of innovation and creativity within the workplace, knowledge development empowers employees with the latest knowledge, contributing to a dynamic work environment and positively impacting their well-being. In the ever-evolving landscape of employee well-being, knowledge development emerges as a dynamic and transformative force. This exploration unveils key variables shaping professional growth and overall satisfaction. On-the-job training offers continuous learning, fostering competence. A structured professional development plan contributes to career advancement and a sense of purpose. The inclusion of a retirement development plan instills

a sense of security. Workshops and training programs contribute not only to professional expertise but also to personal growth.

These factors described below are outlined below and will be applied in this study to assess the impact of AI on South African FM employees:

- On-the-job training: On-the-job training serves as a cornerstone for knowledge development. Employees exposed to continuous learning opportunities within their roles experience professional growth and an enhanced sense of competence.
- Professional development plan: A structured professional development plan ensures systematic skill enhancement and knowledge acquisition. Employees benefit from clear pathways for career advancement, positively impacting their sense of purpose and overall well-being.
- Retirement development plan: Planning for the future, including retirement, contributes to employee well-being. A well-defined retirement development plan supports long-term knowledge development, providing a sense of security and preparedness.
- Workshops and training: Participation in workshops and specialized training programs fosters ongoing knowledge development. These initiatives contribute to professional skills, a sense of accomplishment and personal growth.

Summarily, these key factors – on-the-job training, professional development plan, retirement development plan and workshops and training – remain crucial to collectively shaping knowledge development and its profound impact on the holistic well-being of employees within the organizational landscape.

However, AI adoption within FM organizations would ordinarily result in an increased need for professional development and training on a continuing basis (Yu *et al.*, 2023; Chowdhury *et al.*, 2022). Furthermore, employees' retirement plans have been shown to be disrupted by the adoption of AI in organizations due to the attendant displacement associated with such changes (MacDonald and Weisbach, 2004).

Based on the foregoing, the potential of increased AI adoption by FM organizations to impact these social constructs and by extension, the social well-being of FM employees can be discerned. Considering the unrelenting efforts at increased AI incorporation into FM processes and organizations, an understanding of the impact of AI adoption on employee social well-being has become imperative. Such understanding is essential for the development of a veritable mechanism for managing this reality, allowing for a win-win situation between FM employees and the management of FM organizations.

Recognizing and understanding the nexus between digital technologies uptake and these factors provide a foundation for exploring the impact of AI on the social well-being of FM employees in South Africa. However, a paucity of studies seeking to investigate this nexus within the South African FM context has been observed, especially from a mixed-method methodological perspective. This study adopts a multiplicity of methods to elicit data to investigate this phenomenon within the South African FM context, as it is expected that the impact of increased AI uptake would be mostly felt in developing countries like South Africa, where manual-oriented FM processes remain prevalent.

3. Methodology

A mixed-method research design was utilized in this study for the purpose of understanding the impact of AI on FM employees' social well-being in South Africa. The research

participants consisted of FM organizations that held registration with South African Facilities Management Association (SAFMA).

Given the constrained population size of this study, which comprised 85 organizations registered with SAFMA, the total population sampling (TPS) technique was used to enhance the study's validity. The use of TPS facilitated a comprehensive approach to participant recruitment and ensured the acquisition of dependable data from all well-informed and experienced FM organizations across South Africa.

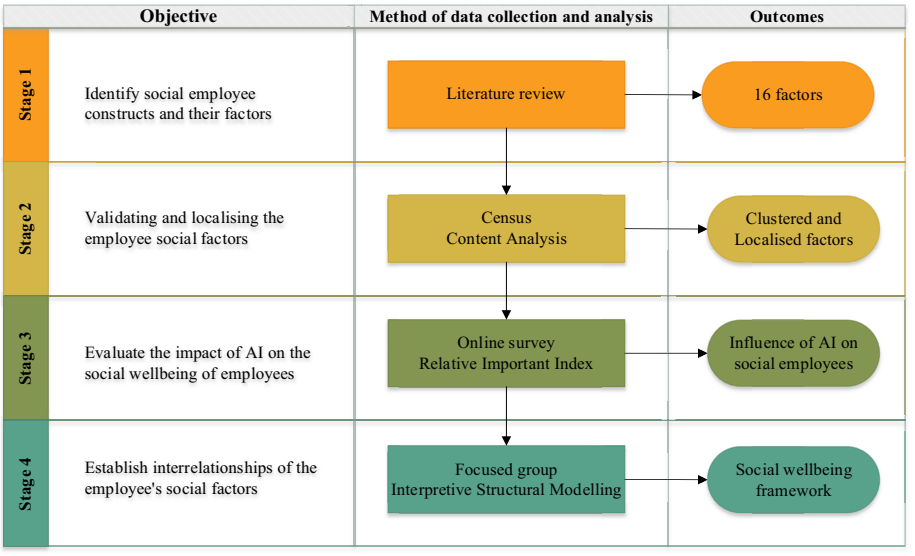
A four-stage approach was meticulously implemented to accomplish the study's objectives. See Figure 1.

Stage 1: Identification of employee social well-being factors affected by AI adoption.

In this stage, key employee social well-being factors influenced by AI adoption within FM organizations were identified from the literature. Relevant literature was systematically sourced from various scientific databases using keywords like "social," "employee," "organization," "artificial intelligence" and "technology." Twenty-seven documents were subsequently selected based on their relevance. The identified documents underwent thorough scrutiny, documenting 16 social well-being related factors that could be impacted by AI adoption. These 16 factors, as presented alongside their sources in Table 1, constituted an initial inventory for measuring the effect of AI on employees' social well-being.

Stage 2: Validating and localizing employee social well-being factors

The primary objective of this stage was to validate and contextualize employee social well-being related factors which could be influenced by AI adoption within the South African context. Due to the subjective nature of social well-being constructs, which rely on the perspectives of different social groups, as noted by Moghayedi *et al.* (2023), it was imperative to validate the social well-being factors for FM employees, originally derived from theoretical foundations, with input from local stakeholders.



Source: Created by author

Figure 1.
Research methodology protocol

Social category	Social factor	Sources
Social relationship	Alienation (SR1)	1–6
	Social isolation (SR2)	2–7
	Work and home-life balance (SR3)	1, 3–4, 6–12
	Social network (SR4)	2–7, 13
	Overwork (SR5)	1, 4, 9–12, 14
Job satisfaction	Autonomy (JS1)	2, 5, 7, 9, 12, 15–17
	Interpersonal relationship (JS2)	2, 5, 7, 13, 16–19
	Job-security (JS3)	2, 9, 13, 20–21
	Organization policy (JS4)	1, 16–17, 22–24
	Professional status (JS5)	1, 13, 16–17, 22
	Remuneration (JS6)	9, 16–17, 19–21
Knowledge development	Task requirement (JS7) On-the-job training (KD1)	9–12, 16–17, 22–23 1, 10–12, 19–20, 23, 25–27
	Professional development Plan (KD2)	1, 19–20, 22–23, 25, 28
	Retirement development plan (KD3)	1, 14, 20, 25, 29
	Workshops and training (KD4)	1, 19–20, 23, 25, 27, 29

Notes: 1. Beer and Mulder (2020); 2. Adibifar (2016); 3. Lam and Lau (2012); 4. Barrett and Baldry (2009); 5. Golden *et al.* (2008); 6. Grimshaw (2007); 7. Valtorta *et al.* (2016); 8. Zhang *et al.* (2022); 9. Connor *et al.* (2018); 10. O'Driscoll *et al.* (2009); 11. Kossek *et al.* (2009); 12. Pfeffer (2009); 13. Drago (2015); 14. Meyer and Maltin (2010); 15. Dong *et al.* (2021); 16. Oduro-Owusu (2010); 17. Stamps and Piedmonte (1986); 18. Yang and Zhao (2018); 19. Bebbington and Dillard (2009); 20. Chowdhury *et al.* (2022); 21. Marzuki *et al.* (2012); 22. Braganza *et al.* (2021); 23. Atkin and Bildsten (2017); 24. Lim *et al.* (2002); 25. Yu *et al.* (2023); 26. Zeytinoglu and Cooke (2009); 27. Bhatt (2001); 28. Kandampully (2002); 29. MacDonald and Weisbach (2004)

Table 1.
Social employee constructs and factors

A semi-structured questionnaire was developed to validate and localize these factors based on the initial 16 factors identified in the literature. These questionnaires were distributed to all FM organizations registered with SAFMA. Representatives of these FM organizations were asked to rank these factors using a five-point Likert scale, ranging from "strongly agree" to "strongly disagree," to indicate the extent to which each social well-being factor held in South Africa and within their respective organizations. Participants were also encouraged to provide reasons and justifications if they disagreed with any specific factor. Furthermore, participants were invited to draw from their professional experience and identify any additional social factors that may not have been covered in the existing literature.

Following the completion of the initial round of primary data collection, it became evident that only 22 out of 85 FM organizations had adopted AI in some manner, resulting in an adoption rate of 26%. Consequently, these 22 FM organizations were considered the sample size for this study. All respondents who participated in the census unanimously agreed that the identified 16 employee social well-being factors were relevant and valid in their respective companies and South Africa, respectively. However, participants provided valuable suggestions for redefining and rewording some factors. For example, the factor "work balance" was redefined as "work and home-life balance" to better align with the local context. See Table 1.

Stage 3: Evaluating the impact of AI on the social well-being of employees.

The objective of this stage was to quantify the impact of AI adoption on employees' social well-being through a broader spectrum of employee perspectives. The feedback received from participating FM organizations formed the foundation for designing a structured questionnaire. This structured questionnaire was subsequently administered to

evaluate the extent to which AI adoption by South African FM organizations impacted the social well-being of their employees.

To facilitate a thorough evaluation with a focus on achieving high response rates, an electronic questionnaire survey was distributed to employees across 22 South African FM organizations that had embraced AI and were involved in the preceding stage. This survey was inclusive, considering participants of all ages, genders and positions within the organizations. Participants were required to assess the impact of AI adoption on their social well-being using a five-point Likert scale, where response options ranged from "very low" (1) to "very high" (5). Due to differences in the size and number of employees across the selected 22 FM organizations, the objective was to collect data from a minimum of 20% of employees from each organization.

Following the data collected from employees of 22 FM organizations, a quantitative analysis was performed using the relative importance index (RII) to quantify the relative importance indices of each social well-being factor. The RII was computed using equation (1):

$$RII = (\Sigma W)/(N \times A)$$

where W represents the weight assigned to each variable by the respondents, ranging from 1 to 5; and N is the total number of respondents. A corresponds to the highest weight, which equals 5.

The RII value ranges from 0% to 100%, with higher values signifying greater importance or influence for the factor. In alignment with Polat *et al.*'s framework, the RII values were categorized into five levels of importance, encompassing both positive and negative influences: high (H) 100%>=RII > 80%, medium-high (M–H) 80%>=RII > 60%, medium (M) 60%>=RII > 40%, medium-low (M–L) 40%>=RII > 20% and low (L) 20%>=RII > 0%,

Stage 4: Establishing interrelationships among employee social well-being factors

The objective of this stage was to thoroughly investigate and establish contextual interrelationships existing among the identified employee social well-being factors, prioritizing them hierarchically and logically using interpretive structural modeling (ISM). This was expected to determine critical employee social well-being factors that would be most impacted by AI adoption from a management perspective.

To facilitate this process, an anonymized virtual focus group discussion session was conducted with expert HR and Technical managers drawn from the human resources and technical departments, who are primarily responsible for technological innovations and well-being in 22 FM organizations that adopted AI. During these discussions, HR and technical managers provided insights into potential relationships among the contextualized employee social well-being factors.

The selected managers engaged in discussions, identifying and deliberating possible contextual relationships existing between the 16 employee social well-being factors. Subsequently, their opinions were organized hierarchically and logically using ISM. ISM is a robust methodology employed to transform complex and poorly articulated models of various systems into straightforward and unambiguous representations (Obi *et al.*, 2020). Its primary purpose is to discern relationships among the considered elements, thus enhancing understanding of a system's structure. ISM is predominantly designed as a group learning process, relying on the group's collective judgment for decision-making. The method is interpretive, as it hinges on the group's judgment to determine whether and how variables are related while simultaneously being structural, as it extracts an overall structure from a complex set of variables based on these relationships (Obi *et al.*, 2020).

ISM involves a series of logical steps, commencing with the development of a structural and reachability matrix, followed by level partitioning to create a diagraph, and concluding with an analysis of structural self-interaction matrices (SSIM) for classification and categorization. The SSIM analysis classifies factors into separate, interdependent and self-governing groups depending on their influence levels. ISM has been effectively used in numerous research endeavors to investigate the connections among these factors and illustrate their hierarchical arrangements visually.

In this study, the ISM methodology played a crucial role in developing a hierarchy of relationships for the validated social employee factors, presenting them graphically based on expert judgments. The experts' perspectives were subjected to thematic analysis and then fed into the ISM procedure. This process resulted in the creation of a reachability matrix, an ISM diagram and a driver power-dependence matrix for the factors related to employee social well-being. The ISM analysis yielded valuable information regarding contextual interdependencies and the varying degrees of influence exhibited by each factor on another. These findings aided the development of the employee social well-being factor model outlined in this research.

4. Findings

4.1 Impact of AI on the social well-being of FM employees

The analysis of survey data from employees of FM organizations, using the RII, is presented in Figure 2. Figure 2 provides a clear view of the RII values, positive or negative influence of AI adoption, overall rankings and the corresponding influence levels for each factor examined within the three primary constructs: social relationship, job satisfaction and knowledge development.

According to Figure 2, job security emerged as the most influential factor, posting an RII of −87.7%. This finding underscores the high negative impact of AI on job security, aligning with previous research that highlighted the negative impact of AI on job security and, consequently, the social well-being of employees (Novo-Corti and Barreiro-Gen, 2015). Following closely, autonomy ranks as the second most impacted by AI adoption, with an RII of 85.3%. Given its inherent connection to the monitoring and reporting process, its high ranking is unsurprising.

Social well-being construct	Employee social well-being factor	RII	Influence	Influence level	Rank in construct	Overall rank
Social Relationship	Alienation (SR1)	-73.3%	Negative	M-H	5	14
	Social isolation (SR2)	-81.6%	Negative	H	2	7
	Work and home-life balance (SR3)	78.0%	Positive	M-H	4	13
	Social network (SR4)	79.8%	Positive	H	3	10
	Overwork (SR5)	83.6%	Positive	H	1	4
Job Satisfaction	Autonomy (JS1)	85.3%	Positive	H	2	2
	Interpersonal relationship (JS2)	81.3%	Positive	H	5	8
	Job security (JS3)	-87.7%	Negative	H	1	1
	Organization policy (JS4)	80.2%	Positive	H	6	9
	Professional status (JS5)	84.7%	Positive	H	3	3
	Remuneration (JS6)	83.2%	Positive	H	4	5
	Task requirement (JS7)	78.7%	Positive	H	7	11
Knowledge Development	On-the-job training (KD1)	70.9%	Positive	M-H	3	15
	Professional development plan (KD2)	82.4%	Positive	H	1	6
	Retirement development plan (KD3)	78.4%	Positive	M-H	2	12
	Workshops and training (KD4)	70.0%	Positive	M-H	4	16

Figure 2.
Impact of AI adoption on employee social well-being factors

Furthermore, the professional status of employees is positively impacted by AI, registering an RII of 84.7%. This impact arises from the profound changes that AI brings to employees' scope of work and responsibilities. Overwork emerges as the fourth factor influenced by AI, with an RII of 83.6%. Employees believe that adopting AI can significantly help improve productivity and work efficiency, thereby reducing instances of overwork. In addition to these factors, remuneration, professional development plans and social isolation also feature prominently in the analysis, with respective RIIs of 83.2%, 82.4% and −81.6%. In contrast, workshops and training, on-the-job training and alienation are considered less affected by AI adoption, receiving relative importance indices of 70.0%, 70.9% and −73.3%, respectively.

As indicated in Figure 2, only three social relationship factors – alienation, social isolation and job security – are adversely affected by AI, whereas the adoption of AI positively influences work and home-life balance and overwork.

Also, the results indicate that AI adoption positively influences all knowledge development factors. In addition, it positively impacts all factors relating to job satisfaction, except job security.

This positioning underscores the nuanced and significant impact of AI adoption, both positive and negative, on the social well-being of employees. It emphasizes the critical roles played by AI in shaping various aspects of employee social well-being and underscores the importance of conducting a thorough study, making necessary preparations and implementing policies by FM organizations before adopting AI. Understanding the degree of impact of AI adoption on employees' social well-being provides FM organizations with valuable insights into AI-employee collaboration managing employees' social well-being, considering the relative importance assigned to these factors by employees. Nonetheless, it is essential to recognize that solely understanding the nature of influence impact does not detail the levels of interdependence and hierarchical significance existing among these factors.

To address this gap, a pair-wise comparison study was conducted using the ISM methodology. This approach facilitated the development of a hierarchical model, providing deeper insights into the interdependence and driving powers among all the identified factors.

4.2 Interpretive structural modeling

A focus group discussion session was organized, involving HR and technical managers in well-being and technological innovation from 22 FM organizations that adopted AI. The primary aim of this session was to determine the contextual relationships among the 16 validated social well-being factors.

During this session, participants were tasked with articulating the relationships between these 16 factors through pair-wise assessments. Specifically, they were instructed to frame these relationships using the contextual relationship statement "will help achieve." These insights provided the basis for constructing the SSIM, a vital tool for illustrating the relationships between two social employee factors denoted as "i" and "j." This matrix employed four distinct symbols to represent these relationships:

V: when factor *i* will help achieve factor *j*.
A: when factor *j* will help achieve factor *i*.
X: when factor *i* and j will help achieve each other.
O: when factor *i* and *j* are unrelated.

The process led to the development of the SSIM.

The symbols V, A, X and O in SSIM were then converted into binaries of 0 and 1 using the rules shown below:

- (i, j) entry in the SSIM is V, then (i, j) entry in the reachability matrix becomes 1
- (i, j) entry in the SSIM is A, then (i, j) entry in the reachability matrix becomes 0
- (i, j) entry in the SSIM is X, then (i, j) entry in the reachability matrix becomes 1
- (i, j) entry in the SSIM is O, then (i, j) entry in the reachability matrix becomes 0

The process began with the creation of the initial binary matrix, which was then used to generate the initial and final reachability matrices, as shown in Table 2. The development of these matrices involved a series of iterations.

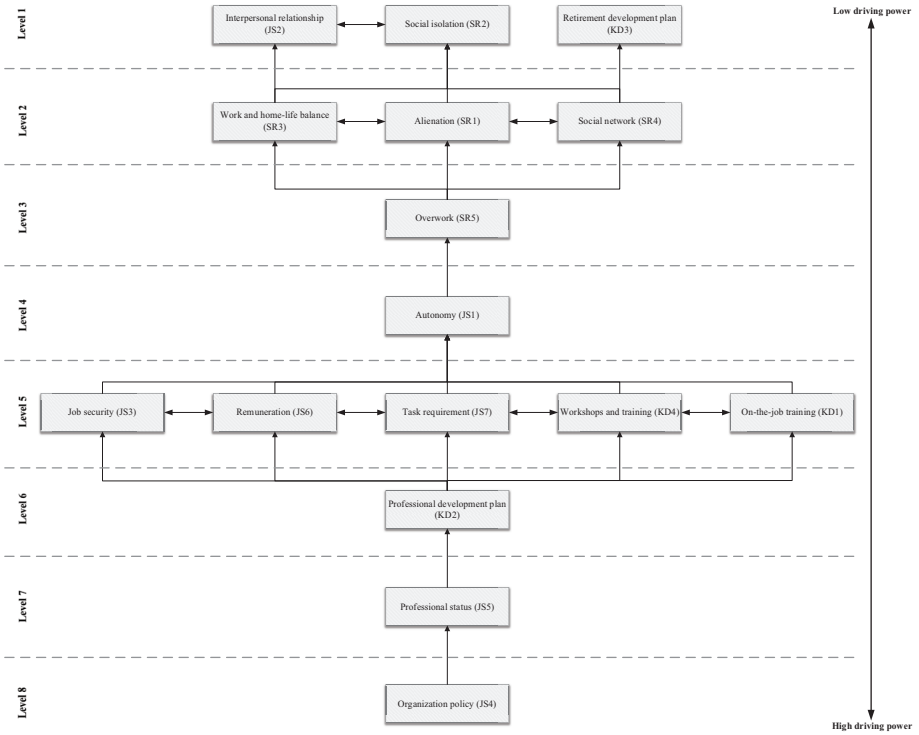
To establish levels within the hierarchy, a level was deemed achieved when the reachability set, comprising a factor and any other factors it might influence, matched the intersecting set. These level partitions ultimately led to the creation of the ISM diagraph, as illustrated in Figure 3.

One of the key advantages of the ISM model lies in its ability to spotlight the most influential factors crucial for attaining employee social well-being through the adoption of technological innovations. Typically, these pivotal factors are situated at the base of the ISM model. Consequently, the factors positioned at the top of the model rely on those at the base for actualization and impact.

The analysis revealed the driving powers and dependencies associated with various factors of employee social well-being, as shown in Table 2. The final reachability matrix establishes the driving power factors set (reachability) and the dependence factors set (antecedent) for each factor. The driving power set of a social factor includes the factor itself and other social factors that may be influenced by it. It encompasses every column marked with "1" in the row corresponding to the social factor under assessment. Conversely, the dependence factors set (antecedent) includes the social factor itself and other factors that may impact it. It comprises every row marked with "1" in the column corresponding to the social factor under examination.

Table 2.
Final reachability matrix

Factor	SRI	SR2	SR3	SR4	SR5	JS1	JS2	JS3	JS4	JS5	JS6	JS7	KD1	KD2	KD3	KD4	Driving power
SRI	1	1	1	1	0	0	1	0	0	0	0	0	0	0	1	0	6
SR2	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	5
SR3	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	6
SR4	1	1	1	1	0	0	1	0	0	0	0	0	0	0	1	0	6
SR5	1	1	1	1	1	0	1	0	0	0	0	0		1	1	1	10
JS1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	7
JS2	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	4
JS3	1	1	1	1	1	1	1	1	0	0	1	1	1	0	1	1	13
JS4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	16
JS5	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	15
JS6	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	14
JS7	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	15
KD1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	15
KD2	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	14
KD3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	2
KD4	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	15
Dependence	15	15	14	15	10	9	14	8	1	5	8	8	9	10	13	9	



Source: Created by author

Figure 3.
Employee social well-being framework

Subsequently, the intersection set for each factor is determined by analyzing their antecedent sets and reachability sets. The first level of social well-being factors is identified based on those factors whose intersection set aligns with the reachability set. This level partitioning process is repeated until the level of each social factor is determined, as illustrated in Figure 4. The first-level enabler secures the top position in the ISM model.

Ultimately, the ISM digraph was developed using the reachability matrix (Figure 4) and the partition levels established (Figure 4).

The ISM diagraph, as illustrated in Figure 3, reveals that "organization policy" was mostly impacted by AI adoption on employees' social well-being.

In Level 8 of Figure 3, the employee social well-being factor "organization policy (JS4)" emerges as the most critical influencer. This factor directly influences "professional status (JS5)," which, in turn, directly impacts on "professional development plan (KD2)" in Levels 7 and 6, respectively. In addition, "organization policy" also plays a role in shaping social factors in Level 5, including "task requirement (JS7), "work and training (KD4)," "on-the-job training (KD1)," "remuneration (JS6)" and consequently "job security (JS3)."

Furthermore, relationships between factors at the same levels can be discerned. In Level 5, bilateral relationships confirm the close correlation between job satisfaction and knowledge development constructs in organizations that have adopted AI. The significance of job satisfaction and knowledge development constructs in using AI is further emphasized by considering that all factors in Levels 8 to 4 are only from these two constructs.

Factor	Reachability set	Antecedent set	Intersection set	Level
Iteration 1				
JS2	7,2,1,4	8,11,10,7,14,2,3,6,9,12,13,1,4,16	7,2,1,4	1
KD3	14,15	8,11,10,14,15,3,5,9,12,13,1,4,16	14,15	1
SR2	7,2,3,1,4	8,11,10,7,14,2,3,5,6,9,12,13,1,4,16	7,2,3,1,4	1
Iteration 2				
SR3	14,3,1,4	8,11,10,14,2,3,5,6,9,12,13,1,8,14,16	14,3,1,4	2
SR1	3,1,4	8,11,10,14,3,5,6,9,12,13,1,4,16	3,1,4	2
SR4	3,1,4	8,11,10,14,3,5,6,9,12,13,1,4,16	3,1,4	2
Iteration 3				
SR5	14,5,13,16	8,11,10,14,5,6,9,12,13,16	14,5,13,16	3
Iteration 4				
JS1	6,16	8,11,10,14,6,9,12,13,16	6,16	4
Iteration 5				
JS3	8,11,12,13,16	8,11,10,14,9,12,13,16	8,11,12,13,16	5
JS6	8,11,14,12,13,16	8,11,10,14,9,12,13,16	8,11,14,12,13,16	5
JS7	8,11,10,14,12,13,16	8,11,10,14,9,12,13,16	8,11,10,14,12,13,16	5
KD1	8,11,10,14,12,13,16	8,11,10,14,9,12,13,16	8,11,10,14,12,13,16	5
KD4	8,11,10,14,12,13,16	8,11,10,14,9,12,13,16	8,11,10,14,12,13,16	5
Iteration 6				
KD2	14	14,9	14	6
Iteration 7				
JS5	10	10,9	10	7
Iteration 8				
JS4	9	9	9	8

Figure 4.
Level partitioning of reachability matrix

On Level 3, "overwork (SR5)" was observed as being more sensitive to and impacted by AI adoption compared to the other four factors of this construct located in Levels 2 and 1.

On Level 2, three social relationship factors, namely, "alienation (SR1)," "work and home-life balance (SR3)" and "social network (SR4)," were observed as having a bilateral relationship with each other, confirming a correlation and direct connection between work and home-life balance and social network to alienation in organizations where employees are using AI.

On Level 1, two factors from social relationship and job satisfaction, namely, "social isolation (SR2)" and "interpersonal relationship (JS2)," showed a bilateral connection, indicating a correlation between these two factors. As shown in Figure 3, "retirement plan development (KD3)" showed the least impact on posted AI adoption.

The analysis was further extended to the 16 social factors using the Matrixed Impacts Croisés Multiplication Appliqué a un Classement (MICMAC) method. This categorization method separates factors into specific groupings based on their driver-dependence characteristics. A factor's driving power signifies the total number of factors, including itself, that it can influence or contribute to. Conversely, dependence indicates the total number of factors that can contribute to the realization of a specific factor. Following the classification methodology used by previous researchers, the autonomous cluster includes variables characterized by low driving and dependence powers. Dependent clusters consist of variables with low driving power but high dependence power. Independent clusters comprise variables with high driving power but low dependence power, while linkage clusters involve variables with high driving and dependence powers. The final reachability matrix was transformed to create the MICMAC diagram. This transformation involved calculating the sum of scores along each corresponding row to determine a factor's power and the sum of scores along each corresponding column to establish a factor's dependence. The results of the MICMAC analysis are presented in Figure 5.

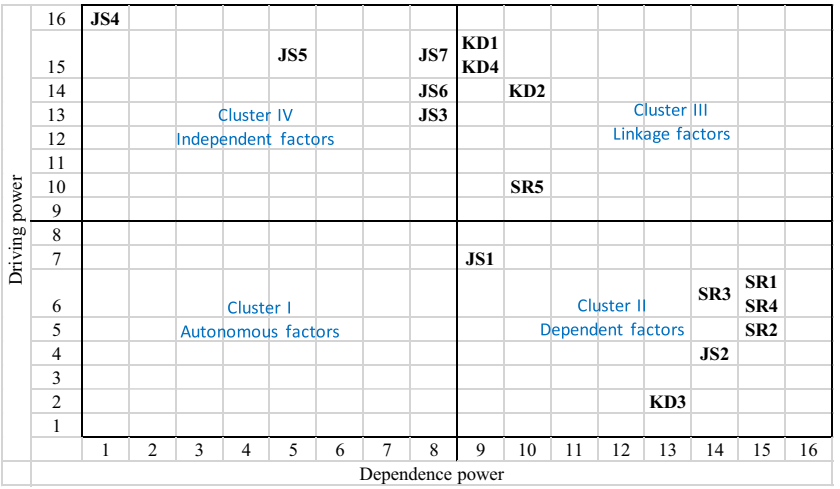


Figure 5.
Classification of employee social well-being factors based on a MICMAC analysis

The 16 social factors have been categorized into four quadrants, as depicted in Figure 5, based on their levels of driving power and dependence. In this representation, the *x*-coordinate represents the degree of dependence power, while the *y*-coordinate signifies the extent of driving power.

The first quadrant, "autonomous cluster," comprises social factors characterized by weak driving power and weak dependence. Factors in this quadrant typically operate independently of the system and have limited connections to other social factors (Obi *et al.*, 2020). As illustrated in Figure 5, no social well-being factor falls within this quadrant. This indicates that none of the identified social well-being factors in this study assumes the position of a disconnected entity from other social well-being factors.

The second quadrant, "dependence cluster," encompasses social well-being factors with weak driving power but strong dependence on other factors. According to Figure 5, four out of five social relationship factors – alienation (SR1), social isolation (SR2), work and home-life balance (SR3) and social network (SR4) – are situated in this quadrant. This positioning elucidates the dependence of social relationship factors, particularly on job satisfaction factors. Moreover, two job satisfaction factors – autonomy (JS1) and interpersonal relationship (JS2) – along with a retirement development plan (KD3) from knowledge development, are also located in this quadrant. This indicates their dependence on other social well-being factors. Specifically, the retirement development plan (KD3) is purely dependent on other social well-being factors.

The third quadrant, referred to as the "linkage cluster," consists of social factors characterized by both strong driving power and strong dependence. These factors are closely interconnected and mutually reliant, implying that actions or changes in one factor will have an impact on others (Obi *et al.*, 2020). The social well-being factors identified within the linkage cluster include three from the knowledge development construct – on-the-job training (KD1), professional development plan (KD2) and workshops and training (KD4) – along with overwork (SR5). Given their inherent instability, any AI influence on these factors is likely to have a cascading effect, affecting other factors and the overall social well-being of employees in organizations that adopted AI.

The fourth quadrant, "independent cluster," encompasses social factors with strong driving power but weak dependence. Out of the seven job satisfaction factors examined in this study – job security (JS3), organization policy (JS4), professional status (JS5), remuneration (JS6) and task requirement (JS7) – five fall within this quadrant. This observation underscores the pivotal role and influential nature of job satisfaction factors, especially organizational policy, in driving the adoption of AI and shaping its social impacts on employees, as illustrated in Figure 5.

5. Discussion and implications

The study set out to elicit the perceptions of employees of South Africa FM organizations on the impact of AI adoption on their social well-being. Furthermore, it determined the nature and degree of influence posted by AI adoption on these factors using the perceptions of these employees. Finally, it established the interrelationship between these factors of social well-being that are impacted by AI adoption.

From the study's findings, it can be discerned that the adoption of AI by FM organizations exerts a substantial mixed influence, encompassing both positive and negative aspects, on various social well-being factors, with impacts ranging from high to medium-high. The findings strongly highlight the positive impact of AI on 13 social well-being factors, compared to only three factors where a negative impact was observed. The top three social factors influenced by AI adoption, job security, autonomy and professional status, are paramount for employees' social well-being. Job security is deemed fundamental for establishing enduring social relationships. However, it is ranked as the most negatively impacted by AI adoption by employees. This result aligns with findings reported by Lu *et al.* (2016), which emphasized the significance of job security in engendering improved levels of employee social well-being. Furthermore, job security is often associated with remuneration. Little wonder remuneration emerged as the second most highly ranked factor. Yu (2017) highlighted the importance of job security, especially in regions with high unemployment rates and income inequality like South Africa. "Professional status" is ranked third and is of great importance to employees, as the knowledge economy necessitates employees to continually validate their economic value to an organization (Kandampully, 2002; Rasmussen, 2012; Anne Støren, 2016).

Conversely, the three factors least affected by the adoption of AI include alienation (negatively), on-the-job training and workshop and training. While the introduction of AI in organizations can lead to employee alienation, the need for remuneration to meet living expenses seems to influence the lower ranking of "alienation." Training, both on-the-job and in workshops, appears to be less impacted by AI. This suggests that training, being a common component of AI adoption, is well-integrated and has a lesser effect compared to other social well-being factors among employees. In terms of social well-being factor categories, it is noteworthy that four out of the top five factors influenced by AI fall under the job satisfaction category, highlighting the heightened sensitivity of job satisfaction to AI adoption. Conversely, the knowledge development category exhibits lower sensitivity to AI adoption.

Furthermore, the study relied on the ISM methodology and a focus group discussion session to establish the hierarchical nature of the interrelationships between these social well-being factors. HR and technical managers working in the 22 FM organizations participating in the study served as discussants on an online interactive platform. The outcome of this session resulted in the effective categorization of the social well-being factors based on their interrelationships, driving powers and dependence and their subsequent structuring into eight distinct yet somewhat interconnected levels. This

structure is illustrated using the ISM graph. These outcomes highlighted the employee social well-being factors deserving the highest priority in maintaining social harmony among employees within FM organizations during AI adoption. Remarkably, the study identified "organization policy" as the foremost factor to prioritize when striving to enhance the social well-being of FM employees in South Africa. An organization's policy serves as a governance tool, directing decisions toward rational outcomes for the organization (Howlett, 2009; Husin and Hanisch, 2011). It is essential for these policies to exhibit comprehensiveness and capability to accommodate dynamic changes, such as AI adoption, to support an organization's strategic and operational activities (Husin and Hanisch, 2011). However, it is worth noting that, as per Husin and Hanisch (2011), many organizations tend to adopt AI before thoroughly considering the policy implications on employees' social well-being.

Organizational policy lends significant support to fundamental factors such as professional status and professional development plans. Factors deserving a moderate level of priority from organizations include on-the-job training, workshops and training, task requirements, remuneration, job security, autonomy and overwork. Both fundamental factors and those requiring moderate priority are concentrated within the middle tier of the framework. This positioning emphasizes that any positive influence on one of these factors will have a cascading effect, positively impacting other factors at these levels and beyond, particularly on job security, which is the most crucial social factor for employees. In contrast, factors like social network, alienation, work and home-life balance, interpersonal relationships, social isolation and particularly retirement development plans are positioned at Levels 2 and 1 and do not contribute to the attainment of factors situated above their level. This study sheds light on the present realities faced by FM employees during AI adoption within South African FM organizations. Notably, the factors at Level 1 suggest that interpersonal relationships, social isolation and retirement development plans are less sensitive to AI adoption and are not the sole or ultimate concern of employees regarding their well-being. Instead, the findings underscore the multifaceted nature of social well-being in the workplace, emphasizing the critical role of organizational policies as a catalyst for achieving optimal social well-being among employees. The comparison of the level of influence of AI on employee social well-being factor categories and factors, one from across FM employees' perspective regardless of age, gender and positions and the other from the HR and technical management's perspective, highlights the complementary two methods on first identifying and measuring the negative and positive impacts of AI on the social well-being of employees and second on providing a comprehensive plan on the different influence of AI on social factors and determine the independent, dependent and linkage role of various social factors on adoption of AI on social well-being of employees to minimize the adverse impact and maximize the positive impacts – significant disparities in viewpoints within FM organizations. From the overall employees' standpoint, there is a notable emphasis on the substantial impact of AI on job satisfaction factors like adverse influence on job security, positive impact on autonomy and professional status. These social well-being factors are regarded as highly sensitive to AI adoption, indicating their critical role in shaping employee social well-being. On the other hand, management expert employees perceive AI adoption as having a significant influence on organizational policy on the adoption of AI and all other social well-being factors, viewing it as a key independent driver in the social well-being framework, digital transformation of organizations and overall social well-being of employees. Furthermore, management expert employees acknowledge the driving role of job satisfaction factors on job satisfaction factors and, ultimately, the social well-being of employees through knowledge development factors as key linkage variables.

These findings suggest a more balanced and systematic influence of AI adoption on social well-being through appropriate preparation and training of employees prior adopting AI and more notably developing and implementing suitable organization policy for AI adoption to enhance the job security feeling of employees and prove the advantages of AI to employees to enhance their productivity and work balance not a threat, as seen from both viewpoints. These findings align with previous research, which underscores the importance of recognizing the concerns and difficulty of employees on digital transformation and AI adoption which not only influence the employee's social well-being but also their performance and productivity.

Digital transformation, an integral component of the 4IR, is inevitable for FM organizations. However, adopting AI as a pioneering technological innovation without thorough preparation and consideration of its impact on various organizational aspects is inherently risky, as Chowdhury *et al.* (2022) also emphasized. FM organizations must be cognizant of the positive and negative influences of AI, particularly on the social well-being of their employees, and use suitable strategies and actions to address these impacts. The findings presented in this paper assist FM organizations in recognizing both the positive and negative effects of emerging AI on employees' social well-being and highlight social factors that require heightened attention.

Understanding the high-impact potential of AI in facility management allows organizations to optimize their operations through timely AI adoption, leading to swift success. Given the rapid development of technologies and AI, FM organizations are compelled to focus on implementing new digital technologies and AI applications in their operations as expeditiously as possible to reap maximum advantages. However, due to the mixed influence of technologies and AI on organizational and employee performance, FM organizations must carefully strategize the adoption of AI to maximize benefits while minimizing potential adverse effects on the social well-being of employees. This paper aids FM organizations in evaluating and addressing the social well-being impacts of the digital transformation process and AI implementation by proposing an ISM model that delineates the sequence for AI implementation across different tiers.

The study equips FM organizations with a more comprehensive understanding of key social factors impacted by emerging AI technologies, enabling organizations to comprehend AI in the most persuasive and sustainable way. The ISM model serves as a foundational guide for FM organizations and the broader AECO to enhance their practices for a successful, socially responsible digital transformation and AI adoption that prioritizes the well-being of their employees.

6. Conclusion

The adoption of AI and digital transformation necessitates a substantial investment of resources, including finances, time and structural changes within the organization. Therefore, prior to undertaking such initiatives, organizations must carefully assess the positive and negative impacts of AI on their overall operations, with a particular focus on the well-being of their employees and human resources assets. This assessment should include considerations such as identifying which capabilities or domains should be prioritized for transformation, understanding the key influences of AI on different well-being factors, pinpointing the factors that are more sensitive and require greater consideration, and devising strategies for optimizing the positive impact of AI on employee well-being while minimizing potential negative impacts.

This study aimed to determine the key constructs and factors influencing employees' social well-being, exploring both AI's positive and negative impacts on these social factors.

The research established a hierarchical ISM model, offering FM organizations insights into the influence of AI on their employees' social well-being. This process resulted in a hierarchy of importance across five levels, and these factors were categorized based on their power-dependence clusters through a MIC-MAC analysis. This approach culminated in the development of a social well-being framework for employees, shedding light on the key factors and primary drivers of employee social well-being within South African FM organizations. Additionally, the study provides implementation suggestions to mitigate negative impacts and maximize the benefits of AI adoption. MICMAC analysis categorized the identified social factors into three clusters: independent, dependent and linkage. Notably, the research findings emphasize the substantial impact of AI on job satisfaction factors, necessitating the adoption of well-defined organizational strategies through effective policy formulation to mitigate the negative effects of AI on employees' social well-being.

Moreover, this research presents significant opportunities for FM organizations in the realm of digital transformation, emphasizing the importance of adopting AI while ensuring the preservation of employees' social well-being. Given the initial survey's indication of a relatively low level of AI adoption in South African FM organizations and recognizing that AI adoption in these organizations is still in its early stages, the study's findings are specifically relevant to the initial phases of AI adoption. These findings may undergo changes as AI becomes more widely accepted and integrated into the operations of FM organizations.

While this study focused on the context of South African FM organizations, its findings can be applied to a broader spectrum of AECO organizations and the adoption of other innovative technologies associated with 4IR. This research significantly contributes to the body of knowledge related to social sustainability by providing insights into the factors that affect the adoption of technological innovations and their intricate contextual relationships. AECO organizations across the Global South can leverage the identified factors to enhance the social well-being of their employees, serving as a valuable reference for further investigations tailored to their specific regions.

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