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Employee well-being in robot, artificial intelligence and service automation-integrated workplace: A scoping review

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Orientation: The integration of Robot, Artificial Intelligence and Service Automation (RAISA) has transformed the workplace, reshaping work processes and efficiency. However, RAISA also brings complex implications for employee well-being.

Research purpose: This study aimed to explore determinants, intervening variables and theoretical frameworks associated with employee well-being in RAISA-integrated workplaces through a scoping review.

Motivation for the study: Despite the rapid expansion of RAISA, research on its impact on well-being remains fragmented. A scoping review provides a structured synthesis to guide future research and inform practical strategies, including human resource management (HRM) initiatives that foster well-being.

Research approach/design and method: Peer-reviewed studies were sourced from Scopus, Web of Science, EBSCOhost, PubMed and Taylor & Francis. Following predefined inclusion and exclusion criteria, 35 studies were charted to answer the research questions.

Main findings: Employee well-being in RAISA contexts is affected by personal factors (e.g. awareness, efficacy, job insecurity) and organisational factors (e.g. leadership, job design, support systems). Mediators and moderators such as self-efficacy, emotional responses and leadership styles influence how these factors relate to well-being. Theoretical frameworks, like Job Demands-Resources (JD-R) Model and Self-Determination Theory (SDT), offer robust explanations of the dynamic interactions between studied variables.

Practical/managerial implications: The review highlights the need for HRM to balance RAISA's efficiency gains with strategies that support employee health, development and resilience.

Contribution/value-add: By synthesising fragmented literature, this study provides a comprehensive foundation for future research and offers valuable insights for organisational strategies to manage human impacts of RAISA, particularly regarding well-being.

Keywords: well-being; employee; smart technology; artificial intelligence; robot; automation; workplace; scoping review.

Introduction

The Volatility, Uncertainty, Complexity and Ambiguity (VUCA) era drives companies to exert additional effort to achieve their objectives effectively. Lie et al. (2023) stated that a key measure of this achievement is organisational performance, which requires companies to deliver exceptional results to adapt and thrive in the fast-evolving business context. Moreover, superior organisational performance can only be obtained through superior employee work performance. Consequently, Human Resource (HR) management practices should prioritise the effort to ensure that employees' work performance is always exceeding the organisation's target, and in turn, contributing a positive impact towards organisational performance (Saraswati et al., 2023). Research shows that employees perform optimally when experiencing positive psychological well-being, which significantly influences both individual performance and productivity (Handayani et al., 2022; Kim et al., 2018; Lee et al., 2021; Sheeran et al., 2025; Zelenski et al., 2008).

World Health Organization (2005) described well-being as a condition in which a person recognises their own capabilities, can handle everyday life challenges, works efficiently and effectively, and contributes meaningfully to their community. In the hedonic perspective, subjective well-being pertains to an individual's general evaluation of life and emotional experiences, including life satisfaction, positive affect and minimal negative affect (Diener et al., 2015). Meanwhile, the eudaimonic perspective was adopted to develop the concept of psychological well-being, defined as an individual's psychological health based on the fulfilment of criteria for positive psychological functioning (Ryff, 2023).

The work environment contributes greatly to shaping employee well-being, particularly because of the unique challenges it presents. Anglin et al. (2018) concluded that promoting employee well-being is associated with improving the environment where the employee works, which then results in a job that is valuable, motivating and pleasant. In simpler terms, employees who work in a safe and stress-free work environment will exhibit optimal work performance. One such challenge is the increasing integration of technology in the workplace, which is often aimed at improving operational efficiency and reducing costs (Lee et al., 2021).

Among the various technologies adopted in recent decades, robots, artificial intelligence and service automation (RAISA) have gained prominence for its ability to identify patterns, make decisions and optimise work processes (Webb, 2019). In particular, a robot is identified as a system which can influence its surroundings by grasping and repositioning objects around it (Nikolova et al., 2024). Artificial intelligence (AI) refers to systems that exhibit smart responses by analysing their environment and, with a certain level of autonomy, performing actions aimed at achieving defined goals (Sheikh et al., 2023), while automation is defined as the replacement of human involvement in processes, procedures or equipment with automatic operation (Gerovitch, 2003).

Robots, artificial intelligence and service automation has been largely adopted in industrial settings, as reflected in a survey report conducted in 2025, revealing that 77% of 32 352 participants reported that their organisation had implemented RAISA in the work process. Moreover, 58% of the participants pointed out that they used RAISA for task completion on a regular basis (Gillespie et al., 2025). Closer examination found that RAISA has been applied in various industries to enhance the efficiency of repetitive and routine tasks within distinct workplace settings. For instance, in the manufacturing sector, robots are utilised as material and equipment automatic movers in factories and warehouses (Webb, 2019). In the tourism industry, AI is commonly employed to enhance customer service through human–AI interactions, such as assisting guests with travel planning and in-room services (Loureiro et al., 2023). Additionally, routine customer queries may be handled via chatbots or automated telephone routing systems (Henkel et al., 2020).

Empirical studies have shown that RAISA usage in the workplace, on the one hand, helped to promote employee well-being, such as dealing with difficult customers (Jiang et al., 2022; Willems et al., 2023). Robot, artificial intelligence and service automation was also perceived as a useful resource as it supports employees to complete routine and repetitive tasks (Stamate et al., 2021). Thus, employees had more free time for self-development and high-value innovations (Akter et al., 2024). Regarding self-development, employees perceived RAISA integration as an opportunity for career as well as skill enhancement (Konuk et al., 2023; Tong et al., 2021). On the other hand, the integration of RAISA at work could also reduce employee well-being as it acts as a job demand. Robot, artificial intelligence and service automation was proven to create work stress (Loureiro et al., 2023) and general health (Nazareno & Schiff, 2021). Employees needed to adapt to the new technology by investing more time in learning how to operate the new technology installation as it became part of their job requirements (Kong et al., 2021; Stamate et al., 2021). Furthermore, the automation led to workplace isolation because of the limitation of personal interaction between employees (Nurski & Hoffmann, 2022; Tang et al., 2023). Technical issues with regard to the integration of new technology created additional workload that led to work stress (Hang et al., 2022). Robot, artificial intelligence and service automation was also perceived as a threat because employee believes that it would replace their position doing routine tasks in the organisation (Schwabe & Castellacci, 2020).

Studies examining the impact of RAISA on well-being have produced mixed findings, suggesting that RAISA may function either as a supportive resource or as a potential risk factor. Considering the growing role of RAISA integration in shaping employee well-being, a scoping review is necessary to systematically map existing studies in this area. To the extent of our knowledge, no scoping reviews on employee well-being have specifically examined the integration of RAISA in workplace contexts. Existing reviews have largely emphasised the effects of broader technological domains, such as social media and general technology use, on individual well-being in settings such as healthcare (Aparicio et al., 2025; Lemahieu et al., 2025; Widjaya & Komara, 2023). Closer to the present scope, several reviews have addressed RAISA-related areas, including machine learning, social robots and AI-based conversational agents (Ghafurian et al., 2025; Li et al., 2023; Yang & Zou, 2025).

While the aforementioned reviews offer important perspectives on the intersection of technology and well-being, they do not capture the unique implications of RAISA, which introduces new forms of human–technology interaction in organisational settings, towards employee well-being. This gap highlights the need for a scoping review that consolidates current knowledge on employee well-being in the work environment with RAISA adoption. Such a review not only clarifies the state of the literature but also establishes a direction for future empirical research and organisational practices in the era of smart technology. Therefore, the purpose of this study was to: (1) carry out a scoping review on employee well-being in RAISA-integrated workplace, (2) map out the included studies and (3) provide recommendations, both for future research as well as practical strategies.

Research design

Research method

According to Peters et al. (2021), a scoping review is an appropriate method for mapping existing evidence in a given field. Accordingly, this study conducted a scoping review to examine the literature on employee well-being in workplaces implementing RAISA and to systematically map and report the findings. The insights obtained from this review are expected to be beneficial not only theoretically but also practically. According to the guidance of the Joanna Briggs Institute (JBI), a scoping review should employ methodological steps, including (1) review question identification, (2) protocol development, (3) search strategy, (4) study selection, (5) data extraction and (6) analysis and presentation of results (Peters et al., 2021).

The review questions for the current scoping review were developed by analysing the literature gaps and the study's objectives. The JBI recommends formulating review questions by considering the Population, Concept and Context (PCC) framework to ensure more focused questions (Peters et al., 2021). In this study, the population is employees, the concept is well-being and the context is RAISA. Hence, the current scoping review formulated the review questions as:

- What factors affect employee well-being in workplaces integrated with RAISA?
- Which intervening variables act as mediators or moderators in the association between the determinants and well-being?
- What theoretical frameworks have been applied to study employee well-being in RAISA-based work environments?

Once the review questions were formulated, the authors registered the review protocol before conducting the scoping review (Peters et al., 2021). The protocol of this study was registered through www.osf.io on 09 December 2023. The pre-registered protocol is available at https://doi.org/10.31219/osf.io/e98jk.

The search strategy was initially developed by identifying keywords aligned with the PCC framework, ensuring a focused and systematic retrieval of relevant studies. Thus, the keywords generated for the search strategy were ('well-being' OR 'wellbeing' OR 'ill-being' OR 'illbeing') AND ('AI' OR 'artificial intelligence' OR 'automation' OR 'robot' OR 'RAISA' OR 'STARA' OR 'RAIA') AND 'employee*'. Two reviewers conducted the search on 17 March 2025 and obtained 1232 articles, described as follows: (1) Scopus (364 articles), (2) Web of Science (337 articles), (3) EBSCOhost (26 articles), (4) PubMed (65 articles) and (5) Taylor and Francis (440 articles). All retrieved articles were imported into Zotero, a reference management software. The deduplication process was carried out using this software, resulting in a total of 989 articles.

Study selection was initiated by exporting the deduplicated articles to Rayyan (https://rayyan.ai). In this process, reviewers are supposed to make decision regarding which article to be included in the scoping review, by referring to the predetermined inclusion as well as exclusion criteria, shown in Table 1.

The study selection was carried out by two reviewers and any disagreements regarding study inclusion were resolved through discussion between the first and second reviewers. If discrepancies remained, they would be escalated to the third reviewer who provided the final decision (Peters et al., 2020). The first stage of screening involved reviewing the abstracts of all retrieved articles. Articles were excluded if they did not align with the inclusion criteria. As a result, the number of articles was reduced to 85. In the second stage, a full-text review was carried out using the same inclusion and exclusion criteria, ultimately resulting in 35 articles to be included in the final report. Quality assessment was then carried out by referring to AXIS, an evaluation instrument designed to measure the quality of cross-sectional studies (Downes et al., 2016). AXIS consisted of 20 indicators, which were clustered into (1) introduction, (2) methods, (3) results, (4) discussion and (5) others. Articles to be included are ones with a low risk of bias.

Data charting was carried out following the quality assessment process. Articles were then extracted and charted in a table. In scoping reviews, charted data are commonly organised in tables or diagrams to create a structured overview of the evidence base, which helps in identifying key concepts and research gaps (Cooper et al., 2021). The charting table should present key information, including author(s), references and results relevant to the review questions (Peters et al., 2021). The extracted information charted in the table of the current scoping review were

TABLE 1: Inclusion and exclusion criteria.

Criteria	Inclusion criteria	Exclusion criteria
Focus	Research focused on measuring the impact of determinant variables of employee well-being in the workplace with RAISA adoption	Research not focused on measuring the impact of determinant variables of employee well-being in the workplace, with RAISA adoption, like academic settings and within technology users aside from RAISA, like those using smartphones, computers and other devices
Population	Employee	Other groups of participants, including students, the elderly, hospital patients and others
Objective of research	Research that measured the impact of determinant variables on employee well-being in the RAISA-integrated work environment	Research that did not measure the impact of RAISA and its determinant variables on employee well-being, such as social media and internet usage
Research design	Quantitative	Non-quantitative research methods, including interviews, observations and reviews
Reporting	Studies that clearly identify the measured factors and present detailed results of the statistical data analysis	Research article not specifically describing the factors that it measured and without presenting the specific result of statistical analysis of the data
Article retrieval	The complete article is readily accessible as well as retrievable	Complete article is neither inaccessible nor retrievable
Language	Published in English	Publications in non-English languages (e.g. Chinese, Arabic, Turkish)

RAISA, robot, artificial intelligence and service automation.

authors and publication year, geographical location of the study, the number of recruited participants and research findings.

This scoping review employed both descriptive and thematic analyses as an analytic strategy. Descriptive analysis was used to summarise the characteristics of the included studies, offering an overview of existing research on employee well-being in the work environment integrated with RAISA. Thematic analysis, following Braun and Clarke (2006), was conducted to identify and synthesise recurring patterns across the literature. Data were inductively coded, organised into themes and sub-themes and iteratively refined to ensure coherence and clarity. Themes were then discussed in relation to the review questions, with illustrative examples provided to highlight key findings and research gaps. The themes and sub-themes employed in the analysis section are described in Table 2.

Ethical considerations

This article does not contain any studies involving human participants performed by any of the authors.

Results

An overview of the selected studies

From the initial search across five databases, a total of 1232 articles were identified. After deduplication using Zotero, 248 duplicates were removed. An eligibility assessment was then conducted with the aid of an automation tool (https://rayyan.ai), which excluded an additional 193 articles. The automation tool facilitated the screening process by pre-assessing study type, publication source, participants and research methods. In the first stage of study selection, namely abstract screening, 706 articles were excluded, leaving 85 articles for further assessment. Because of the limited accessibility of five full texts, 80 articles were reviewed in detail, of which 35 were ultimately deemed eligible for inclusion in the final review and analysis. The selection results and the reasons for excluding certain articles are illustrated in the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) flowchart (Figure 1).

A total of 35 peer-reviewed studies were included in this review. Sourcing for articles in this scoping review was not restricted by publication year. However, the included research articles were issued between 2018 and 2025, reflecting the increasing scholarly attention to employee well-being in the workplace with RAISA integration. Sample sizes ranged from 120 to 21 689 employees, drawn from industries such as logistics and healthcare. Most of the studies were carried out in Asia, while a smaller number involved multicountry or multicontinent contexts. All studies relied on self-report questionnaires as the primary method of data collection. Table 3 presents key information that covers the characteristics of the included studies.

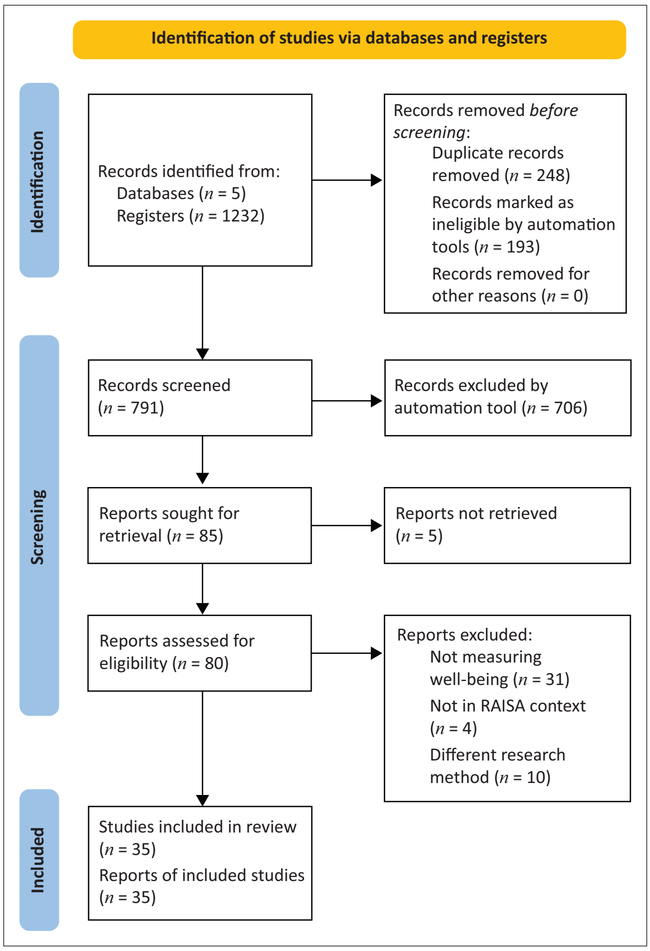
TABLE 2: Themes and sub-themes.

Themes	Sub-themes
1. Determinants of employee well-being in RAISA-integrated workplace	1.1 Individual level 1.2 Organisational level
2. Intervening variables of employee well-being in the RAISA-integrated workplace	2.1 Individual level 2.2 Organisational level
3. Theoretical frameworks to describe the employee well-being in the RAISA-integrated workplace	3.1 Contextual 3.2 Psychological

RAISA, robot, artificial intelligence and service automation.

Determinants of employee well-being in robot, artificial intelligence and service automation-integrated workplace

Taking a closer look at the data charted in Table 2, the determinants of employee well-being are discussed by classifying them into two domains: personal and organisational domains. On the personal level, this scoping review has successfully identified key factors influencing employee well-being. Firstly, prior research considered variables assessing employees' ability to adapt to RAISA integration in the workplace. These factors include AI efficacy, AI-assisted digital skills and general mental ability. Secondly, previous studies also examined employees' perceptions of RAISA integration, whether positive or negative. Positive perceptions were measured through variables such as Smart Technology, Artificial



Source: Adapted from: https://www.prisma-statement.org/prisma-2020-flow-diagram.

FIGURE 1: Preferred reporting items for systematic reviews and meta-analyses diagram of study record and selection.

TABLE 3: A summary of included studies.

No.	Author(s) and year	Country	Population	Findings
1	Brougham and Haar (2018)	New Zealand	120	STARA awareness is positively correlated with depression (β = 0.25, p < 0.05) and cynicism (β = 0.34, p < 0.001).
2	Stamate et al. (2021)	Canada	546	AI can be viewed as a job resource (β = 0.727, p < 0.01), challenge (β = 0.680, p < 0.01) or hindrance (β = 0.424, p < 0.01). When seen as a resource, AI significantly predicted the satisfaction of basic psychological needs (β = 0.120, p < 0.05), while as a hindrance it predicted need thwarting (β = 0.195, p < 0.01); need satisfaction in turn increased well-being (β = 0.390, p < 0.01) and reduced distress (β = −0.179, p < 0.01), whereas need thwarting reduced well-being (β = −0.209, p < 0.01) and heightened distress (β = 0.440, p < 0.01).
3	Jiang et al. (2022)	China	516	Smart technology positively influences corporate trust (β = 0.319, p < 0.05), self-efficacy (β = 0.292, p < 0.05) and employee well-being (β = 0.104, p < 0.05), with self-efficacy (β = 0.341, p < 0.05) and corporate trust (β = 0.391, p < 0.05) directly enhancing well-being and smart technology exerting an indirect effect on well-being (β = 0.108779, p < 0.05).
4	Kinowska and Sienkiewicz (2020)	European countries	21 869	Algorithmic management negatively affects workplace well-being both directly (β = 0.09, p < 0.001) and indirectly through reduced job autonomy (β = 0.18, p < 0.001) and total rewards (β = -0.04, p < 0.001). Job autonomy (β = 0.59, p < 0.001) and total rewards (β = 0.41, p < 0.001) positively contribute to workplace well-being as well.
5	Kong et al. (2023)	China	447	Employee–AI collaboration enhances career satisfaction (β = 0.32, p < 0.01) and mediates the positive effect of AI trust on career satisfaction.
6	Konuk et al. (2023)	Turkey	606	Job-replacement anxiety does not affect psychological well-being (β = 0.024, p > 0.05, while AI learning anxiety (β = 0.077, p < 0.05), emotive dissonance (β = 0.91, p = 0.003 < 0.01) and emotive effort (β = 0.160, p < 0.001) have significant effects. Autonomy weakens the emotive dissonance's negative impact (R^2 = 0.030, p < 0.01) on psychological well-being.
7	Loureiro et al. (2023)	Portugal	200	Employee happiness is an indirect implication of benign stress, mediated by employee engagement (β = 0.238; p < 0.001).
8	Shaikh et al. (2023)	Pakistan	184	AI has a significant contribution towards employee mental health as well as well-being (β = 0.206, t = 2.469, p = 0.014).
9	Tang et al. (2023)	Taiwan, Indonesia, the United States, and Malaysia	794	Employees may respond to increased AI interaction at work adaptively (β = 0.34, p < 0.001) by exhibiting more affiliative behaviours like helping (β = 0.35, p < 0.001) because of heightened affiliation needs or maladaptively through isolating behaviours such as alcohol consumption (β = 1.28, p = 0.033) and insomnia (β = 0.34, p < 0.001) driven by increased loneliness.
10	Willems et al. (2023)	Belgium	165	Employee well-being is negatively impacted by heavy physical work (β = 0.20; $BCCI_{95\%}$ = [0.36; 0.02]) and repetitive mental tasks (β = 0.17; $BCCI_{95\%}$ = [0.30; 0.02]. Job security and career opportunities (β = 0.34; $BCCI_{95\%}$ = [0.20; 0.47]), clearly defined roles (β = 0.20; $BCCI_{95\%}$ = [0.07; 0.31]) and participatory decision-making (β = 0.15; $BCCI_{95\%}$ = [0.02; 0.06]) positively contribute to well-being.
11	Xu et al. (2023)	China	268	Informal learning in the workplace functions as a partial mediator of the association between AI opportunity perception and employee well-being (effect = 0.17, 99% CI = 0.10–0.28). Unemployment risk perception also functions as a moderator on the link between AI opportunity perception and informal learning (β = −0.35, p = 0.000).
12	Yang and Gao (2023)	China	332	Co-creation with service robots positively influences employee well-being by enhancing autonomy (β = 0.013, p < 0.05), which mediates its impact on the need for relatedness and, in turn, further strengthens employee well-being (β = 0.178, p < 0.01).
13	Aulia and Lin (2025)	Indonesia	286	AI-assisted digital skills strengthen human–AI teaming (β = 0.605, p < 0.001), task–technology fit (β = 0.573, p < 0.001) and perceived e-leadership support (β = 0.502, p < 0.001). These factors subsequently enhance employee well-being, with human–AI teaming (β = 0.239), task–technology fit (β = 0.448) and perceived e-leadership support (β = 0.247) all showing positive effects.
14	Chang et al. (2024)	China	301	Challenge technology stressors show a positive correlation with positive affect (β =0.56, p < 0.001), while hindrance technology stressors increase AI anxiety (β =0.52, p < 0.001). Technical self-efficacy moderating both relationships by strengthening the positive effect on affect (β = 0.51, p < 0.001) and mitigating AI anxiety (β = −0.37, p < 0.001).
15	Chen et al. (2024)	China	479	Competency needs (r = 0.135, p < 0.01) and job embeddedness (r = 0.126, p < 0.01) positively impact well-being.
16	Farzana and Liu (2024)	US	215	Perceptions of AI opportunities show a strong positive relationship with both informal workplace learning (β = 0.525, T = 8.462, p < 0.001) and employee workplace well-being (WWB) (β = 0.292, T = 3.285, p = 0.001). However, the perception of unemployment risk does not significantly contribute as a moderator towards the correlation between AI opportunity perception and informal learning (β = 0.005, T = 0.105, p = 0.916).
17	Jeong et al. (2024)	South Korea	375	Coaching leadership serves as a negative moderator, reducing the potential increase in job stress that may arise from AI adoption (β = −0.305, p < 0.001).
18	Jin et al. (2024)	China	349	STARA awareness negatively contributes to employees' work affective well-being (β = −0.258, p < 0.001), with job stress mediating this relationship (β = −0.140, p <0.01). Psychological resilience is a significant moderator to weaken the association between STARA awareness and job stress (β = −0.194, p < 0.01).
19	Kim and Lee (2024)	South Korea	416	Job stress significantly mediates the relationship between AI adoption and burnout, with AI adoption significantly increasing job stress (β = 0.286, p < 0.001). Self-efficacy in AI learning moderates this effect by reducing the impact of AI adoption towards job stress (β = −0.215, p < 0.001).
20	Kim et al. (2024)	South Korea	408	Job insecurity affects employee depression directly and indirectly (β = 0.13, p < 0.05), through psychological safety as mediator (β = −0.17, p < 0.01). Self-efficacy in AI use serves as a moderator on this relationship by buffering the impact of job insecurity towards psychological safety (β = 0.28, p < 0.001).
21	Meduri et al. (2024)	India	320	AI integration is significantly correlated to employee burnout (β = 0.214, p = 0.000), but well-trained employees (β = 0.507, p = 0.000), personalised AI tools (β = 0.343, p = 0.000), and AI feedback help reduce burnout levels (β = 0.076, p = 0.000).
22	Soomro et al. (2024)	Pakistan	324	Organisational support (β = 0.0120, p < 0.05) and manager capability (β = 0.062, p < 0.05) help to reduce the impact of AI anxiety towards employee well-being.
23	Tan et al. (2024)	China	235	Only the hindrance perspective of AI resulted in a positive correlation with workplace anxiety (β = 0.155, p < 0.05).
24	Turja et al. (2022)	Finland	535	In robotised workplaces, higher job satisfaction is correlated to job diversity (R^2 = 0.085), depending on the extent of time employees spend working with robots.
25	Weng et al. (2024)	China	322	Responsible AI serves as a key driver of positive employee well-being as frontline service employees perceive it as a positive signal that enhances their perception of ethics for care of the organisation (β = 0.694, t = 18.469, p = 0.000).
26	Wu et al. (2024)	China	350	Job insecurity has a positive impact on tech-learning anxiety (β = 0.29, p < 0.001), which leads to reduced well-being (β = −0.28, p < 0.001). Workplace mindfulness moderates these effects (β = −0.45, p < 0.001), making the indirect negative impacts significant when mindfulness is low.

Table 3 continues on the next page →

TABLE 3 (Continues...): A summary of included studies.

No.	Author(s) and year	Country	Population	Findings
27	Zhou et al. (2024)	China	820	AI awareness is related to negative emotional responses (β = 0.430, p < 0.001). Promotion (β = 0.298, p < 0.001) and leadership (β = 0.237, p < 0.001) are successfully functioning as a buffer.
28	Arboh et al. (2025)	Ghana	420	AI awareness enhances employees' informal learning (β = 0.166, p < 0.001), thereby improving workplace well-being. This relationship is further reinforced by learning orientation, which strengthens both the direct and indirect effects of AI awareness on well-being via informal learning (β = 0.0932, p < 0.05).
29	Chuang et al. (2025)	Taiwan	600	Generative AI adoption reduces technostress (γ = 0.19, p < 0.01), and its negative impact on exhaustion (γ = 0.33, p < 0.01), while AI efficacy enhances job satisfaction by increasing engagement (γ = 0.50, p < 0.01), with a serial mediation effect correlating generative AI, technostress, exhaustion (effect = 0.017, 95% CI = 0.031, 0.007) and job satisfaction (effect = 0.043, 95 % CI = 0.024, 0.066).
30	He et al. (2023)	US and China	USA: 173 China: 271	Collaboration with robots influenced self-esteem threat positively (b = 0.36, SE = 0.06, p < 0.001), which mediated its effect on burnout. Perceived intelligence of robots functioned as a moderator on this indirect effect (estimate = 0.06, SE = 0.03, 95% CI [0.003, 0.13]).
31	Kim and Lee (2025)	South Korea	421	Organisationally prescribed perfectionism has no significant direct effect on generalised anxiety disorder (β = 0.040, p > 0.05), but job stress mediates this relationship (β = 0.447, p < 0.001). Self-efficacy in AI use weakens the impact of organisationally prescribed perfectionism on job stress (β = −0.215, p < 0.001).
32	Sehgal et al. (2025)	India	275	Social robot anthropomorphism promotes employees' psychological well-being (b = 0.084, p = 0.015) via social robot warmth as mediator (effect = 0.473, p < 0.05), with technology readiness moderating both mediation effects (b = 0.165, t = 4.802, p < 0.05).
33	Sharif et al. (2025)	China	277	Technostress moderates the association of AI use and employee well-being (β = 0.115, p = 0.05), as well as the link between AI use and job insecurity, affecting well-being (β = 0.036, p < 0.001).
34	Yang et al. (2025a)	China	331	Employees working with service robots experience lower work well-being than those collaborating with humans. Workplace loneliness mediates this effect by hindering workplace friendships and negatively impacting well-being (β = 0.219, SE = 0.061, 95% CI [0.099, 0.339], not included 0).
35	Yang et al. (2025b)	Taiwan	2814	Poor mental health and burnout were reported more common among employees who experience techno-insecurity ([OR = 1.78; 95% CI, 1.37–2.30; p < 0.01], [OR = 1.87; 95% CI, 1.45–2.41; p < 0.01]) and techno-strain ([OR = 2.19; 95% CI, 1.68–2.85; p < 0.01], [OR = 2.20; 95% CI, 1.70–2.83; p < 0.01]).

Note: Please see the full reference list of this article: Saraswati, K.D.H., Fajrianthi, F., & Sami'an, S. (2025). Employee well-being in robot, artificial intelligence and service automation-integrated workplace: A scoping review. SA Journal of Industrial Psychology/SA Tydskrif vir Bedryfsielkunde, 51(0), a2323. https://doi.org/10.4102/sajip.v51i0.2323 for more information.
STARA, Smart Technology, Artificial Intelligence, Robotics, and Algorithms; AI, artificial intelligence; SE, standard error; OR, odds ratio; CI, confidence interval; US, United States.

Intelligence, Robotics, and Algorithms (STARA) or AI awareness, AI trust, job resources, AI opportunity perception, challenge technology appraisal and stressors. Conversely, negative perceptions were assessed through factors such as job skill demands, job demands, hindrance technology appraisal and stressors. Lastly, as outlined in Table 2, several studies also explored emotional and attitudinal responses to RAISA, including AI anxiety, benign stress, job insecurity, techno-strain and techno-insecurity.

The first key topic in the organisational domain is RAISA integration itself. This aspect is evaluated using variables such as AI usage, the adoption of AI and generative AI, algorithmic management, AI and smart technology, interaction frequency with AI and social robot anthropomorphism. For instance, Tang et al. (2023) found that interactions with AI can encourage employees to exhibit more helpful behaviours at work. The second topic pertains to job design, which has undergone transformation because of RAISA integration in the workplace (Nurski & Hoffmann, 2022). This includes changes in work mode, job diversity, collaboration and co-creation with robots, work intensity, personalisation, feedback mechanisms and training. Yang et al. (2025a) observed that employees who work with robots tend to exhibit lower well-being than those who collaborate with human colleagues. Furthermore, organisations set distinct work expectations regarding RAISA integration, including AI responsibility and prescribed perfectionism. When implemented with positive intent, RAISA has been shown to empower employees, foster a fair business environment and enhance customer and societal trust. As a result, RAISA integration within organisations serves as a crucial factor in promoting employee well-being.

Intervening variables of employee well-being in robot, artificial intelligence and service automation-integrated workplace

A large proportion of the studies examined in this scoping review incorporated intervening variables, functioning either as mediators, moderators or in some cases both, to better illustrate the correlation between RAISA implementation and well-being. A significant proportion of these variables is rooted in personal factors, reflecting individual psychological and emotional capacities that influence how employees perceive and respond to RAISA. Examples include resilience, self-efficacy, emotional labour, loneliness, technological anxiety, psychological safety and job stress, as well as more nuanced constructs such as self-esteem threat, social robot warmth and workplace loneliness**.** These variables highlight the centrality of employees' attitudes in determining whether RAISA is experienced as a supportive tool or a stressor in the workplace. In addition to personal-level factors, several studies emphasised the role of organisational factors as intervening mechanisms. These include structural supports and practices such as AI adoption, human–AI collaboration, task–technology fit, organisational support, coaching leadership, perceived e-leadership support and employee–customer interaction quality. Such factors indicate that RAISA's impact on well-being is not merely an individual experience but also shaped by the broader work environment and organisational strategies. Furthermore, job-related variables such as job challenge, job autonomy, job resources, job hindrance, unemployment risk perception, technostress and workplace mindfulness were identified as significant conditions that moderate or mediate employee responses. Together, these findings suggest that the interaction between RAISA and employee well-being is highly contingent upon both personal and organisational aspects, with intervening variables acting as explanatory mechanisms for diverse outcomes of well-being.

Theoretical frameworks to describe employee well-being in robot, artificial intelligence and service automation-integrated workplace

Researchers used a theoretical framework for explaining how determinants and intervening variables influence employee well-being. This scoping review has summarised theoretical frameworks used in previous studies with regard to employee well-being in the work environment integrated with RAISA. The theoretical framework is discussed within two domains: contextual and psychological. In the contextual domain, employee well-being is illustrated according to a change in job design and organisational system because of the integration of RAISA. The most common theory employed in the included articles is the job demands-resources (JD-R) theory. This theory posits RAISA as job resources (e.g. autonomy, trust) as well as job demands (e.g. risk of unemployment, technostress), emphasising that RAISA integration in the workplace might be reflected as motivating or burdening factors. Previous studies also illustrated how RAISA affects employee well-being in the conservation of resources theory. This theory underlines that stress emerges from how employees feel or predict that they will lose their valued resources (e.g. job insecurity, competency needs). The Technology Acceptance Model (TAM) explains how employees develop acceptance and intention to use RAISA as a tool to support their work tasks. It describes a sequential process that begins with employees' evaluation of RAISA-based on its perceived usefulness, and eventually leads to its actual utilisation in the workplace. In the context of RAISA, TAM highlights that successful integration relies not only on technical capability but also on how employees evaluate its relevance and usability, making their perceptions a critical factor in ensuring that RAISA adoption supports both performance and well-being.

The psychological domain highlights the psychological experiences because of the integration of RAISA at work. This includes motivational theories such as Self-Determination Theory (SDT), explaining that employees' motivation will increase when RAISA usage fulfils their basic needs, namely autonomy, competence and relatedness. The example of variables included in the studies is job autonomy and job insecurity to explain how RAISA is perceived as a factor that will or will not satisfy employees' basic needs. Affective event theory further demonstrates how daily interactions with RAISA can trigger both positive emotions (e.g. reduced stress through robot assistance) and negative ones (e.g. anxiety because of AI learning). Another theory which is widely used is the theory of stress. Integration of RAISA is perceived as a stressful situation that affects employee well-being. When RAISA is perceived as a stressor that exceeds their coping resources, work stress occurs. On the contrary, when an organisation supports RAISA integration effectively, the smart technology is seen as a facility that helps employee (e.g. benign stress) to enhance their happiness at work. Overall, the contextual and psychological frameworks highlight that employee well-being in workplaces with RAISA cannot be explained by a single perspective. Instead, it emerges from the dynamic interaction between environmental demands and resources, as well as individual cognitive and motivational processes.

Discussion

Several notes are being taken regarding the scoping review results presented above. The findings will be discussed in threefold: (1) the determinants, (2) intervening variables and (3) theoretical frameworks in the included studies.

Previous research on employee well-being in the workplace with RAISA integration has included personal as well as organisational factors as determinants. On the personal level, the determinants focus on how RAISA affects the employees' psychological aspects, such as perception, emotion, attitude and behaviour. Integrating RAISA in the workplace will somehow affect employees because they are in contact with the smart technology on a daily basis. Employees' perceptions towards RAISA may be different from one another. When they perceive RAISA as a resource that assists them in work completion, employees will experience a positive emotion that, in turn, leads to positive work attitude and behaviour (Huang & Rust, 2018). On the contrary, when they perceive it as a demand, RAISA will cost them effort and add up their workload. Moreover, employees will experience a negative emotion and, consequently, negative work attitude and behaviour will occur (Frey & Osborne, 2017; Nurski & Hoffmann, 2022).

The determinants on the organisational level focus on the organisation's decision to integrate RAISA as part of its business strategy. The advancement of technology is often evaluated as an opportunity to create a more efficient mechanism in organisations, including work culture and employee workflows. Therefore, RAISA will help them to promote the organisation's productivity and overall performance. Rather than resulting positively, the integration of RAISA has changed job characteristics that lead to a shift in how employees perceive their jobs (Nurski & Hoffmann, 2022). And as illustrated above, employees' perception towards RAISA will then affect their well-being.

The second fold of our discussion emphasises variables, which intervene in the correlation between the determinant factors and employee well-being in the context of RAISA integration. Across the reviewed studies, intervening variables were present in most cases, whether they function as a moderator, a mediator or even both. According to Baron and Kenny (1986), a moderator is an intervening variable that affects how two variables are related to each other. In certain cases, the moderator may change the direction of correlation as well. Baron and Kenny (1986) also presented an explanation of a mediator, which explains the mechanism through which a predictor influences an outcome. In general, it was concluded that moderators determine when an effect is likely to occur, while mediators describe how or why the effect happens.

Given the functional description of mediating and moderating variables, involving intervening variables in the research model will clearly enrich our understanding of how each variable may affect the correlation. As illustrated by the JD-R model, personal factors – or personal resources – help employees to have access to more job resources. In this context, personal resources are defined as positive self-evaluation that refers to an individual's appraisal of their capability to effectively control and influence their environment (Bakker et al., 2023). In this sense, when an employee is faced with a new situation like RAISA, they are going to need their own resources to deal with the uncertainties and demands. Therefore, their well-being will remain high. For instance, self-efficacy plays an important role as a buffer to promote employee well-being because it mitigates employees' anxiety while dealing with the new technology, like RAISA (Chang et al., 2024).

On the other hand, organisational factors affect employee well-being as they may be perceived in a different way. For example, initially organisation implements AI adoption in order to create a more efficient work process. Conversely, employees may perceive it as a threat to their well-being because the adoption of AI will cost them extra effort to learn and adapt to the new technology installation (Wu et al., 2024). Furthermore, RAISA is possibly perceived as a substitute for their existence, which may cause them to lose their current job (Sharif et al., 2025). Hence, adding up these factors as intervening variables will help us to have a better understanding of the factors to leverage or degrade the effect of RAISA integration on employee well-being.

Finally, this scoping review has summarised theoretical frameworks that help to describe the mechanism of how the variables interact with each other from a different perspective. As an example, the JD-R theory is used to illustrate that the integration of RAISA is perceived as a job demand as well as a job resource. Job demands refer to the physical, psychological, social or organisational characteristics of work that require continuous physical, mental and/or emotional effort, which may lead to physiological or psychological strain. In contrast, job resources encompass the physical, psychological, social or organisational aspects of work that provide motivational value, support the achievement of work objectives, help buffer the impacts of job demands and enhance learning as well as personal development (Bakker et al., 2023). In this sense, RAISA integration is perceived as a demand when it develops a negative assumption, including unemployment risk perception, AI anxiety and technostress. Consequently, it affects employee well-being negatively. On the contrary, when perceived as a job resource, RAISA creates a motivational situation such as corporate trust, job autonomy and employee engagement.

The theory of stress is commonly used to give an overview of employee well-being in the context of RAISA. Stress occurs when there is a mismatch between external and internal pressures and the individual's available resources or skills to manage them (Lazarus, 1993). Although the integration of RAISA can be very demanding because of its complications and employees' lacking skills, when sufficient support is provided, RAISA facilitates how employees work and generates happiness in the workplace (Loureiro et al., 2023).

As an opposition to Lazarus and Folkman's theory of stress, the conservation of resources (COR) theory claims that individuals aim to gain, maintain, develop and protect the resources they value most. This theory suggests that stress arises in three situations: (1) when important resources are at risk of being lost, (2) when essential resources have already been lost or (3) when significant effort is made to obtain key resources but fails (Hobfoll et al., 2018). When an organisation implements RAISA to take over certain tasks from employees, it can heighten the loss of their career resources, promoting the perceived threat of RAISA to their job security. As employees become more aware of RAISA, their job stress may rise, which could negatively impact their affective well-being at work (Jin et al., 2024).

Another theory used as a framework in the studies is SDT. This theory suggests that satisfying the three basic needs of competence, autonomy and relatedness places individuals in an optimal condition of well-being (Deci et al., 2017). Stamate et al. (2021) gave further explanation that RAISA is related to the satisfaction of employees' basic needs, thus it will also affect their well-being. In this case, RAISA is opening more opportunities for employee to learn new knowledge and skills to operate the smart technology (competence), adding to their liberty for better time management because RAISA supports them with administrative work (autonomy), and increasing positive collaboration through real-time feedback (relatedness).

Overall, the determinants, intervening variables and theoretical frameworks reviewed in this study illustrate that employee well-being in a work environment with RAISA implementation is shaped by a complex interaction of contextual conditions, personal resources and theories. This highlights the need for a multidimensional perspective that not only captures direct influences but also accounts for mediating and moderating mechanisms, thereby offering a more holistic understanding of how RAISA transforms the dynamics of work and well-being.

Limitations of current scoping review and future research direction

As revealed through the findings of this scoping review, the limitations of this review and suggestions for future research will be discussed in this section. Firstly, in terms of database coverage, this scoping review only used five databases: Scopus, Web of Science, EBSCOhost, PubMed and Taylor & Francis. The review could be improved by incorporating additional databases (e.g. APA PsycNet), which specialise in psychology-related research. In addition, grey literature (non-traditionally published materials, including Google Scholar articles, institutional repositories, conference proceedings and preprints) was not included. Including these sources would enhance the comprehensiveness of the review, as it would incorporate a broader range of studies and perspectives.

Secondly, the concept of well-being used in all studies does not fully adopt the established well-being frameworks. Some included studies use job satisfaction, burnout and depression as well-being indicators, which do not necessarily align with widely recognised well-being perspectives, such as the hedonic or eudaimonic approach. A more focused scoping review on well-being would benefit from explicitly adopting a theoretical framework, ensuring that only studies aligning with a specific well-being concept are included. Furthermore, empirical research suggests putting more attention on the approach of well-being. The included studies have not measured eudaimonic well-being, a situation where an individual focuses on an ideal psychological state, indicated by excellence, personal growth, meaning and purpose in life (Gutiérrez et al., 2020). This approach will definitely expand our comprehension on balancing the technology advancement with self-development, including job competency and career orientation.

Thirdly, this scoping review aimed to reveal the determinants, intervening variables and theoretical framework employed in the previous studies. Future reviews could be expanded to cover other aspects of the studies, such as: (1) research instruments, giving an overview of the scales to measure well-being; (2) research designs, presenting a detailed information whether the studies are experimental, longitudinal or cross-sectional; and (3) research gaps, narrating the areas that have not been explored in existing studies on employee well-being. Including these elements in a scoping review will be beneficial for future researchers to develop a sound research model and design for employee well-being in the RAISA context.

Conclusion

This scoping review identified determinants, intervening variables, well-being concepts and theoretical frameworks utilised in 35 previous studies on employee well-being within the RAISA context. Generally, these studies examined various variables at both individual and organisational levels. The findings reinforced the notion that employee well-being in RAISA-integrated work environment is an impact of both personal and organisational factors. Moreover, the development of research models was largely shaped by theoretical frameworks. These frameworks played a crucial role in explaining the interactions among the variables examined in the studies.

Ultimately, this scoping review aims to offer valuable theoretical and practical insights for stakeholders. Future research on employee well-being in workplaces embedded with RAISA should be further refined. Future scoping reviews could explore additional themes and sub-themes, such as measurement tools, research gaps, methodologies and data analysis strategies. This would enable a more comprehensive mapping of existing studies on employee well-being in the RAISA context and generate sharper recommendations for future research. From a practical perspective, human resource management (HRM) should prioritise employee well-being in response to smart technology integration. Potential negative impacts can be reduced by carefully addressing determinants and intervening variables when designing interventions. Such programmes may focus on personal development, including skill enhancement and career management. Skill enhancement consists of upskilling (improving and/or expanding existing skills) and reskilling (learning new skills), while career management consists of developing career path programme, not only vertical but also cross-functional assignment. The objective is to ensure that employees are equipped with the necessary competencies and clear career expectations to adapt to rapidly evolving technologies.

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CRediT authorship contribution

Kiky D.H. Saraswati; Conceptualisation, Data curation, Resources; Writing – original draft; Fajrianthi Fajrianthi: Conceptualisation, Writing – review & editing, Validation; Sami'an Sami'an: Conceptualisation, Writing – review & editing, Validation. All authors reviewed the article, contributed to the discussion of results, approved the final version for submission and publication, and take responsibility for the integrity of its findings.

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Data availability

The authors confirm that the data supporting the findings of this study are available within the article.

Disclaimer

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