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# The AI Frontier: Mapping and Prioritizing the Drivers and Challenges of Generative AI in Employee Engagement

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## Abstract

Organizations are rapidly adopting Generative Artificial Intelligence (GenAI) for significant productivity gains, yet they are often not ready for its serious negative impacts on the workforce. This creates a major challenge for management. There is a significant research gap regarding the paradoxical effect of GenAI, where technological advancement undermines the employee psychological safety. This study directly addressed this gap by investigating the overall effect of this dual impact on employee engagement. A mixed-methods design was employed, combining a PRISMA-compliant systematic review of 27 articles with the Best-Worst Method applied to the judgments of eight organizational experts. Findings revealed a clear contrast. While knowledge management, dynamic content generation, and workflow automation were confirmed as positive drivers of job engagement, their benefits were significantly offset by specific risks. Ethical concerns, privacy breaches, and widespread distrust emerged as significant negative factors that substantially weaken engagement, resulting in technostress, cognitive overload, and job insecurity. Based on these findings, we proposed a conceptual-empirical framework for human-centered GenAI integration. The study concluded that without implementing robust data governance and specific measures to manage technostress, the potential of GenAI will not be realized, leading to widespread and persistent employee disengagement.

## Keywords

Artificial Intelligence (AI), Employee Engagement, Digital Human Resource Management, Best–Worst Method (BWM)

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## Introduction

AI, particularly GenAI, has profoundly reshaped workplace dynamics and human–system interactions, enhancing organizational productivity and accelerating the transition toward a knowledge-based economy (Banh & Strobel, 2023; Clear et al., 2025; Feuerriegel et al., 2024). By redesigning work practices, GenAI offers immense potential to boost both efficiency and employee well-being (Brynjolfsson & Raymond, 2025; Marimon et al., 2025). However, realizing this potential requires navigating complex human resource (HR) dynamics, primarily employee engagement. Defined as a deep emotional, cognitive, and behavioral attachment to organization (Chidambaram et al., 2025; Kahn, 1990), engagement is a crucial driver of sustainable growth (Hanaysha, 2016; Kerdpitak & Jermsittiparsert, 2020), and has received significant attention from researchers (Yuan, 2025).

Despite its importance, the global status of the employee engagement is alarming. Only 21% of employees worldwide are engaged, costing the global economy approximately 9.6 trillion USD annually (Gallup, 2025). In the era of digital transformation, hybrid work arrangements, and shifting workforce demographics (such as Generation Z), sustaining engagement is no longer merely a performance strategy, but a fundamental necessity for talent retention and organizational survival (Anitha, 2014; Donelan, 2023; Dutta et al., 2023; Gallup, 2022; Kadao & Balkrishna, 2025; Motyka, 2018; Richard, 2024; Saxena & Mishra, 2025; Sharma & Goyal, 2022; Tortorella et al., 2025;Xu et al., 2021).

As engagement levels decline, organizational leaders face mounting pressure to leverage AI effectively (Crabtree, 2018; Gallup, 2025; van Vulpen et al., 2024). However, the impact of GenAI on engagement is inherently dual and can be understood through the lenses of the Job Demands-Resources (JD-R) theory and Social Exchange Theory (SET). On one hand, GenAI can act as a valuable job resource, empowering employees and fostering a positive social exchange within the organization. On the other hand, if poorly implemented, it may increase job demands, intensify work pressure, and weaken occupational identity (Liu & Cheng, 2025; Liu & Li, 2025; Sun & Bunchapattanasakda, 2019). Despite this complexity, the multilevel pathways through which GenAI influences engagement remain insufficiently explored (Arora & Damarla, 2025; Goswami & Upadhyay, 2019; Herlina et al., 2024; Liu et al., 2025; Mehta & Jadhav, 2023).

Exploring this complex dynamic is particularly critical in developing countries and under challenging economic conditions (Gallup, 2023), where macroeconomic turbulence exacerbates HR challenges, making technology adoption a high-stakes endeavor (Kumar et al., 2023; Ohemeng et al., 2020; Tensay & Singh, 2020,). A prominent example is Iran, where the employee engagement rate stands at a mere 11%—nearly half the global average (Gallup, 2025). In such a volatile economic environment, organizations desperately need innovative solutions. GenAI could serve as a strategic catalyst to overcome productivity bottlenecks and severe human capital challenges, provided its implementation is carefully managed.

While recent studies predominantly emphasized GenAI's direct impacts on operational efficiency (Khan et al., 2024; Prasad & Dey, 2024), there is a significant empirical void regarding the deeper psychological and organizational mechanisms that govern its effect on employee engagement. To address this critical research gap, this study shifts the focus from purely technical outcomes to human-centric impacts, posing the following research question:

*What are the underlying mechanisms explaining the effect of GenAI on employee engagement?*

To answer this question and advance the theoretical boundaries, this study adopted a mixed-methods design. By integrating a systematic literature review (SLR), thematic analysis, and empirical weighting, this research developed a novel and comprehensive framework. This study contributes to the HRM literature by unpacking the underlying dimensions of the dual effects of GenAI through established theoretical lenses, while also providing practical and prioritized guidance for organizational policymakers navigating emerging technologies. Furthermore, given that previous research has highlighted the gap between developed and developing economies in leveraging the capabilities of GenAI (Dubay, 2026), the findings of this study may provide context-specific insights for organizations operating in developing economies, including Iran. The applicability of these priorities to other contexts may also prove valuable.

## Literature Review

### GenAI

GenAI, as the most advanced application of deep learning, has redefined the notion of the "doer of work" in knowledge-intensive jobs through its capacity to generate novel, human-like content (Banh & Strobel, 2023). Its defining distinction lies in the shift from a traditional decision-support tool to an active contributor that operates at both system and application levels, shaping task execution and employee work experiences in ways increasingly comparable to human input (Chowdhary & Chowdhary, 2020; Feuerriegel et al., 2024).

From a sociotechnical systems perspective, GenAI functions as a reconfiguring force that transforms both the content of work and employees' subjective experience of it (Banh & Strobel, 2023). By actively participating in idea generation and problem solving, it embodies a dual nature: it can reduce cognitive burden through the automation of mental processes, yet it also intrudes into domains once regarded as exclusively human (Susarla et al., 2023). Importantly, its organizational consequences depend less on technical capability than on how employees perceive it (Alabi et al., 2024). Perceived control, transparency, and interpretations of technological agency shape whether GenAI is experienced as an empowering resource or a threat (Einola & Khoreva, 2023). Accordingly, any account of GenAI's organizational role remains incomplete without attention to its attitudinal and psychological implications, making it a critical point of departure for understanding the dynamics of employee engagement. In this study, the focus is exclusively on GenAI. Therefore, whenever concepts such as chatbots, large language models (LLM), natural language processing (NLP) tools, or other AI-based technologies are mentioned throughout the manuscript, they are interpreted within the context of the capabilities and applications of GenAI and are considered as subsets of it.

### Employee Engagement

Despite the early conceptual fragmentation in the literature (Saks & Gruman, 2014), employee engagement was formally articulated by Kahn (1990) as the simultaneous physical, cognitive, and emotional investment of individuals in their work roles. Kahn's psychological conditions framework (1990) linked engagement to the experience of meaningfulness, safety, and availability. Schaufeli and Bakker (2004) further conceptualized it as a positive, fulfilling, and relatively persistent state of mind. A major theoretical refinement was introduced by Saks (2006), who distinguished between job engagement and organizational engagement, emphasizing that employees' attachment to their work tasks does not necessarily imply attachment to the broader organization.

Contemporary research generally agrees that, although employee engagement overlaps with related constructs such as job satisfaction, organizational commitment, and job involvement, it remains a distinct, dynamic, and relational construct (Saks, 2006; Saks & Gruman, 2014). Drawing on the dominant streams of engagement research, it can be understood as a multidimensional state emerging from reciprocal employee–organization interactions, through which employees voluntarily invest their cognitive, emotional, and physical resources in their work and organizational roles (Chidambaram et al., 2025).

Extensive empirical evidence confirmed the employee engagement as a strategic variable with tangible performance outcomes. Large-scale and longitudinal studies by Gallup (2026) and Harter et al. (2002) showed that highly engaged business units simultaneously achieve stronger financial outcomes, including productivity and profitability, customer-related outcomes such as satisfaction and loyalty, and operational outcomes including lower turnover and fewer workplace incidents. From a HRM perspective, engagement is therefore more than a "soft" indicator. It functions as a critical mediating mechanism through which HR practices translate into sustainable competitive advantages (Jangbahadur et al., 2025; Kumar & Pansari, 2016). This mechanism is particularly salient in service-intensive industries, where the quality of human interaction directly shapes the customer experience (Alabi et al., 2024).

Based on the broader literature, the drivers of employee engagement can be organized into a three-level framework including organizational, job-related, and individual factors (Kahn, 1990; May et al., 2004; Saks, 2006; Sun & Bunchapattanasakda, 2019).

At the organizational level, perceived support, fairness, organizational culture, and leadership style are central. Consistent with SET, the employees' perception that the organization values their well-being creates a reciprocal obligation that fosters engagement (Eisenberger et al., 1986).

At the job level, structural characteristics such as job enrichment, autonomy, and feedback serve as core motivational drivers and key "job resources" within the JD-R model (Bakker & Demerouti, 2007; May et al., 2004; Schaufeli & Bakker, 2004). At the individual level, psychological resources including self-efficacy, resilience, and optimism, operate as catalysts that strengthen the engagement dynamics (Xanthopoulou et al., 2009).

### GenAI and Employee Engagement through Multi-Theoretical Lenses

According to JD-R theory, when GenAI is successfully integrated into the workplace, it functions as an effective job resource. By automating repetitive tasks and enhancing human creativity, this technology reduces the employees' cognitive workload while increasing the resources available for task accomplishment (Goyal et al., 2026; Watanabe et al., 2025). Similarly, from the perspective of SET, when organizations invest in employees' development through the provision of GenAI tools, continuous training and empowerment initiatives are perceived as forms of organizational support. Based on the norm of reciprocity, employees feel obligated to reciprocate this support through greater cognitive and emotional investment in their work, ultimately leading to higher levels of employee engagement (Azeem et al., 2024; Dutta et al., 2023).

In other words, the integration of SET and JD-R framework (Zingnaa, 2020) provides a suitable theoretical foundation for examining the activation of individual, job-related, and organizational drivers (Sun & Bunchapattanasakda, 2019) of the employee engagement.

However, a comprehensive understanding of the paradoxical consequences of GenAI also requires consideration of an opposing perspective, which can likewise be explained through this integrated theoretical lens. According to JD-R theory, the introduction of this technology may unintentionally become a hindering job demand. In such circumstances, by generating cognitive overload, technostress, and job insecurity, GenAI may activate a process that undermines the employee engagement (Watanabe et al., 2025). At the same time, from SET perspective, if the implementation of GenAI threatens the employees' autonomy or is perceived primarily as a means of cost reduction and workforce substitution, it may be viewed as a breach of the psychological contract and a reduction in organizational support. As the quality of the exchange relationship and the level of trust decline, employees may adopt defensive coping mechanisms, resulting in lower levels of employee engagement (Khan et al., 2024).

Therefore, the integration of the JD-R and SET frameworks suggests that GenAI is inherently neither entirely beneficial nor entirely detrimental; rather, it represents a dual-faceted phenomenon. This technology simultaneously influences the balance between job resources and job demands, as well as the quality of the exchange relationship between employees and the organization. Through these mechanisms, GenAI shapes both the direction and the level of employee engagement.

## Methodology

This study employed a mixed-methods design. In the first phase, the SLR was conducted based on the PRISMA framework to identify the impact pathways through which GenAI affects the employee engagement. This framework enabled a structured, transparent, and replicable process for selecting, screening, and analyzing prior studies (Liberati et al., 2009). In the second phase, an empirical expert-based study was carried out to determine the relative importance and priority of the criteria through which GenAI influences the employee engagement. Expert judgments were analyzed using the Best–Worst Method (BWM), one of the most efficient multi-criteria decision-making (MCDM) techniques for small expert samples. BWM was considered appropriate because it requires fewer pairwise comparisons and offers higher consistency than comparable techniques like Analytic Hierarchy Process (AHP) (Rezaei, 2015).

Although the research criteria were inductively extracted through SLR and thematic analysis, the combined JD-R and SET framework provided the conceptual basis for organizing and interpreting them. Accordingly, the identified themes were categorized into facilitating and inhibiting pathways regarding the GenAI's impact on employee engagement. Subsequently, their relative importance was evaluated and prioritized using the BWM.

## Systematic Literature Review

### Source Search

In the identification stage, Scopus, Web of Science, and ProQuest were used as the main databases to ensure the comprehensiveness and credibility of the search process (Nica et al., 2023; Rashid et al., 2023). An advanced search strategy was developed using combinations of keywords related to two core conceptual domains: employee engagement and AI. To enhance the sensitivity and comprehensiveness of the search, the broader term “AI” was used instead of “GenAI”. Drawing on relevant prior studies, the keywords were selected to capture the broadest possible range of publications in the field (García-Navarro et al., 2024; Kelly et al., 2023; Madanchian et al., 2023; Sharma & Chanana, 2025).

The search was limited to studies published in Persian and English, with no restriction on publication year. The process was completed in November 2025. Only articles published in reputable academic journals and conference proceedings were included to ensure the scientific quality and credibility of the sources. In addition, searches using Persian keywords in Google did not identify any relevant Persian-language studies. Overall, the evaluation and selection process began with 1,018 articles, as detailed in the following section.

### Evaluation, Selection, and Analysis of Relevant Studies

During the screening stage, the PRISMA framework was applied to ensure a systematic, transparent, and reproducible process for selecting relevant studies (Moher et al., 2009). The inclusion criteria were defined to retain only studies addressing the role of GenAI in employee engagement. Employee engagement was treated as a construct distinct from related concepts (Christian et al., 2011), and only studies that directly examined engagement within organizational contexts were included.

Ultimately, 25 articles were identified through the database search. Following backward snowballing of their reference lists, two additional articles were added, resulting in a final sample of 27 articles for analysis (see Figure 1).

Although the initial search identified a considerable number of studies, a large proportion of them were excluded after screening because they either addressed AI in general or did not focus specifically on GenAI and employee engagement.

Subsequently, using an inductive approach, the selected studies were examined in depth, and analytical themes and categories related to the role of GenAI in employee engagement were extracted using MAXQDA software. Although interrelated, these themes were conceptually distinct and enabled the identification of how GenAI influences the key drivers of employee engagement.

## BWM

In the empirical phase of this research, MCDM approach—specifically BWM—was employed. As a contemporary technique for weighting criteria based on expert judgment, BWM is particularly suitable for expert-driven studies with limited sample sizes, primarily due to its reduced number of comparisons, lower cognitive load, and higher consistency of judgments.

A review of the previous studies indicated that numerous researches have been conducted within this exact range: panels with fewer than 8 experts (Agrawal & Vinodh, 2021; Anam et al., 2022; Firoozzare et al., 2023; Sahebi et al., 2020), and panels with exactly 8 experts, similar to the current study (Jefroudi & Darestani, 2024; Karmaker et al., 2023).

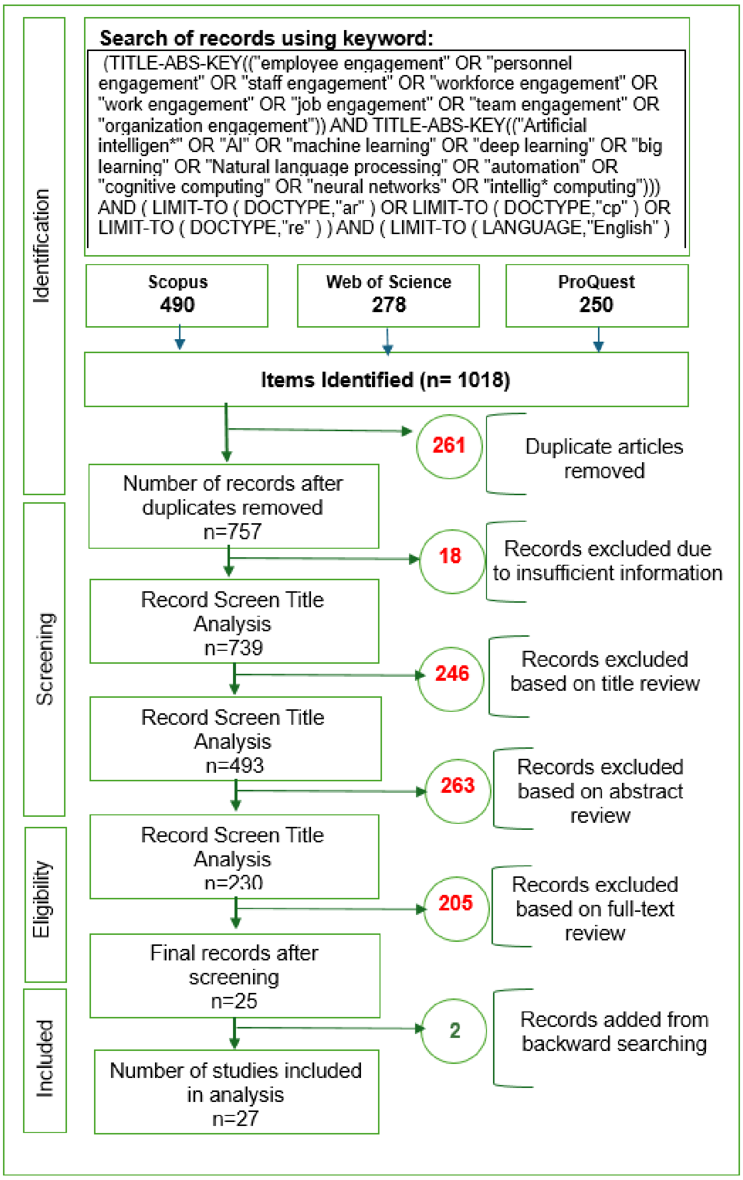
This method is utilized when the objective is to determine the weights of a predefined set of criteria (Rezaei, 2015; Rezaei et al., 2016). According to Rezaei (2015), the implementation of this method involves five steps:

1. Defining the set of criteria: In this study, the criteria pertaining to the facilitating pathways and inhibiting pathways of employee engagement were extracted through SLR.
2. Identifying the best and worst criteria: Experts determined the most important (best) and least important (worst) criteria from the set.
3. Conducting pairwise comparisons**:** Pairwise comparisons were performed between the 'best' criterion and all other criteria via a structured questionnaire. In other words, the preference of the best criterion over the others is determined based on the experts' feedback. This evaluation is conducted using Saaty's nine-point scale (see Table 1).

The resulting Best-to-Others vector is expressed as follows: $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$, where $a_{Bj}$ denotes the preference of the best criterion B over criterion j and $a_{BB} = 1$.

1. Comparing the other criteria with the worst criterion. In the fourth step, pairwise comparisons were conducted between all other criteria and the worst criterion. In the questionnaire, the degree of preference of each criterion over the worst criterion was determined using Saaty's 1–9 scale, as shown in Table 1. The resulting Others-to-Worst vector was defined as follows: $A_w = (a_{1w}, a_{2w}, \dots, a_{nw})^T$, where $a_{jw}$ represents the preference of criterion j over the worst criterion w and $a_{ww} = 1$.

**Figure 1.**
**The PRISMA Flow Diagram**




**(Source: The Researcher's Findings)**

**Table 1.**
**The Scale for Pairwise Comparisons**

| Definition | Intensity of Importance |
|---|---|
| Equal Importance | 1 |
| Moderate Importance | 3 |
| Strong Importance | 5 |
| Very Strong Importance | 7 |
| Extreme Importance | 9 |
| Intermediate values | 2, 4, 6, 8 |

**(Source: The Researcher's Findings)**

2. Determining the criteria weights and consistency ratio. In the fifth step, the final weights of the criteria were obtained by solving an optimization model. The objective was to achieve the greatest possible consistency between the “Best-to-Others” and “Others-to-Worst” comparisons while minimizing deviations from

expert judgments. The output of this step consisted of the optimal weight of each criterion, which provides the basis for the final ranking. In addition, the consistency ratio was calculated to assess the coherence and logical reliability of the expert evaluations. The acceptable consistency values indicated the validity and reliability of the weighting results.

To determine the optimal weight values (w1*,w2*,...,wn*), the optimal weights of the criteria were calculated.

The optimal weight was defined such that, for each pair $\frac{w_b}{w_j}$ and $\frac{w_j}{w_w}$, the relationships $\frac{w_b}{w_j} = a_{Bj}$ and $\frac{w_j}{w_w} = a_{jw}$ hold. To satisfy these conditions for all j, a solution must be found in which the maximum absolute deviations, namely $\frac{w_b}{w_j} - a_{Bj}$ and $\frac{w_j}{w_w} - a_{jw}$, for all j, were minimized. Considering the non-negativity of the weights and the normalization condition (sum of weights), the following optimization problem was obtained.

min ξl

s.t.

$|w_b - a_{Bj}.w_j| \leq$ ξl , for all j

$|w_j - a_{jw}.w_w| \leq$ ξl , for all j

$\sum_j w_j = 1$

Wj ≥ 0, for all j

By solving the above problem, the optimal weights (w1*,w2*,...,wn*) and ξ*were obtained. The larger the value of ξ*, the higher the consistency ratio, indicating that the comparisons were less reliable. The above problem is a linear model that was substituted for the previous non-linear model by Rezaei (2015). A notable advantage of this linear model is the direct calculation of the inconsistency rate without using a consistency index.

### Population and Sample

The statistical population of this study comprised experts employed in three large Iranian organizations that are currently experiencing the practical adoption and use of intelligent assistants based on generative models. These organizations were relatively comparable in terms of digital maturity and the level of organizational intelligentization. Given the practical experience of the organizations included in this study, the findings may be transferable through analytical transferability and may provide useful insights for interpretation in similar organizational contexts and comparable settings.

The combined use of the SLR and the BWM for prioritizing factors related to emerging technologies has also been reported in prior studies conducted in Iranian organizational contexts (Dahooie et al., 2023; Estiri et al., 2025).

A purposive sampling strategy was employed. Ultimately, eight experts with decision-making experience or familiarity with organizational projects related to GenAI participated in the study. In expert-based MCDM methods, small but highly specialized samples are considered appropriate for achieving sufficient analytical adequacy and judgment consistency (Karmaker et al., 2023; Rezaei, 2015).

We applied strict criteria for selecting the experts to ensure that they had an acceptable level of knowledge about the applications of GenAI technology, as well as a relative understanding of the importance of employee engagement. It should be noted that, during the sampling process, only a limited number of experts were found to meet these criteria. Finally, since the approach adopted in this study was based on purposive and judgmental sampling (Rahman et al., 2022), the main emphasis was placed on the depth of expertise and the quality of the feedback rather than on statistical quantity.

The characteristics of the participants are presented in Table 2. To preserve confidentiality, the names of the organizations are not disclosed.

**Table 2.**
**The Characteristics of the Participants**

| ID | Gender | Educational Level | Organization | Position | Area of Expertise | Years of Experience |
|---|---|---|---|---|---|---|
| **1** | Male | PhD | 1 | Director | IT | 18 |
| **2** | Male | Master’s Degree | 1 | Director | IT | 16 |
| **3** | Male | Bachelor’s Degree | 2 | Director | IT | 13 |
| **4** | Male | PhD | 2 | Deputy Director | Executive Management | 22 |
| **5** | Male | PhD | 1 | Director | Digital HR | 19 |
| **6** | Male | Doctor of Professional Studies | 1 and 2 | Consultant | Digital Transformation | 24 |
| **7** | Male | PhD | 3 | Director | IT | 18 |
| **8** | Male | Master’s Degree | 3 | Consultant | IT | 13 |

IT: Information Technology

**(Source: The Researcher's Findings)**

## Findings

### General Characteristics of the Selected Research

The general characteristics of the reviewed sources are presented in Table 3. Their analysis indicated that the existing literature remains nascent and relatively underdeveloped, highlighting a clear need for further research. More than 70% of the articles were published after 2023, reflecting the emerging nature of this field and the rapidly growing scholarly attention to the impact of GenAI on workplace and workforce (Dubey, 2026).

Among the reviewed studies, 17 were journal articles and 10 were conference papers. The relatively high proportion of conference papers suggests that this research domain is dynamic and still evolving. In terms of study type, 20 empirical research articles and seven review studies were identified, indicating simultaneous efforts to generate empirical evidence and develop theoretical conceptualizations. The dominant methodological approach was survey-based research employing advanced statistical techniques like structural equation modeling, whereas qualitative and mixed-methods approaches were less common. Using secondary data such as chat logs and organizational data also remains limited.

**Table 3.**
**The General Characteristics of the Reviewed Sources (R: review ; E: empirical);**

| R. | Authors | Year | Doc. Type | Type of Study | Data analysis | Statistical population | Geogr. Area | Sector |
|---|---|---|---|---|---|---|---|---|
| 1 | Cajander et al., 2026 | 2026 | C | E | Phenomenological | IT Specialist | Sweden | IT |
| 2 | Arora & Damarla, 2025 | 2025 | C | R | Review and Synthesis | - | - | - |
| 3 | Lenka & Chanda, 2024 | 2025 | C | R | Review and Bibliometric Analysis | Scopus | - | - |
| 4 | Srinivas, 2025 | 2025 | C | E | Analytical | Chat Log | India | - |
| 5 | Alzeiby et al., 2025 | 2025 | J | E | Survey and Statistical Analysis | HR Specialist | US | Multiple Industries |
| 6 | Kadao & Balkrishna, 2025 | 2025 | C | E | Survey and Focus Group | Employees | India | Multiple Industries |
| 7 | Watanabe et al., 2025 | 2025 | J | E | Survey and Statistical Analysis | Employees | Japan | Multiple Industries |
| 8 | Trinh et al., 2025 | 2025 | J | E | Survey and Statistical Analysis | Employees | UK and Vietnam | Multiple Industries |
| 9 | Kumar et al., 2025 | 2025 | J | E | Survey and Statistical Analysis | Employees | Fiji | General |
| 10 | Aulia & Lin, 2025 | 2025 | J | E | Survey and Statistical Analysis | Employees | Indonesia | Multiple Industries |
| 11 | Dutta & Mishra, 2025 | 2025 | J | E | Survey and Statistical Analysis | Employees | India | Energy |
| 12 | Wu et al., 2025 | 2025 | J | E | Survey and Statistical Analysis | Employees | China | Hospitality |
| 13 | Hourani, 2025 | 2025 | J | E | Survey and Statistical Analysis | Employees | China | Healthcare |
| 14 | Prasad & De, 2024 | 2024 | J | E | Survey and Statistical Analysis | Employees | India | IT |
| 15 | Estherita & Vasantha, 2024 | 2024 | J | R | Review and Synthesis | - | - | - |
| 16 | Kuznetsov et al., 2024 | 2024 | C | R | Review and Descriptive Analysis | - | - | - |
| 17 | Srivastava & Pandita, 2024 | 2024 | C | E | Interview and Thematic Analysis | HR Specialist | India | Multiple Industries |
| 18 | Khan et al., 2024 | 2024 | J | R | Statistical and Sentiment Analysis | - | - | - |
| 19 | Saouabe et al., 2024 | 2024 | C | R | Qualitative Analysis | - | - | - |
| 20 | Banerjee et al., 2024 | 2024 | J | E | Survey and Statistical Analysis | HR Specialist | US | Multiple Industries |
| 21 | Rane, 2023 | 2024 | J | E | Interview and Co-occurrence Analysis | - | - | HR |
| 22 | Abu-Shanab et al., 2023 | 2023 | C | E | Survey and Focus Group, Statistical and Thematic Analysis | HR Specialist and Employees | Jordan | Agriculture |
| 23 | Paigude et al., 2023 | 2023 | J | E | Analytical | IBM Company's HR Data | - | HR and IT |
| 24 | Dutta et al., 2023 | 2023 | J | E | Survey and Statistical Analysis | Employees | India | - |
| 25 | Kaur & Kaur, 2022 | 2022 | C | R | Descriptive | - | - | - |
| 26 | Marikyan et al., 2022 | 2022 | J | E | Survey and Statistical Analysis | Employees | UK | Multiple Industries |
| 27 | Dutta & Mishra, 2021 | 2021 | J | E | Survey and Statistical Analysis | Employees | India | Multiple Industries |

**(Source: The Researcher's Findings)**

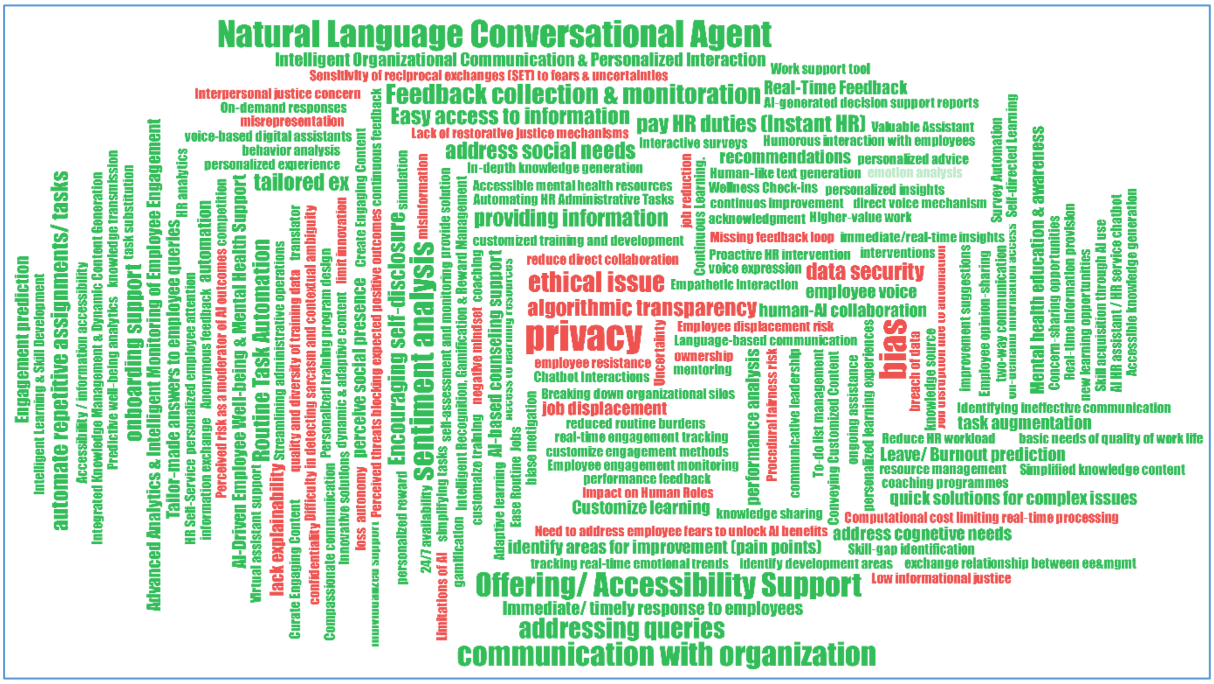
Regarding the study populations, most research focused primarily on employees, followed by HR professionals. No studies based on managerial perspectives were identified, indicating a potential research gap. Geographically, 13 studies were conducted in Asia including seven in India, three in Europe, and two in the United States, while the locations of the remaining studies were unspecified. The numerical dominance of the studies conducted in developing countries compared with advanced economies may limit the generalizability of the findings. In addition, most studies adopted a multi-industry scope.

### GenAI and Employee Engagement

We employed thematic analysis (Braun & Clarke, 2006) on 27 sources to map GenAI's impact pathways on employee engagement. We structured our analysis using the "model, system, and application" framework (Feuerriegel et al., 2024). However, the current literature predominantly reduces GenAI to general-purpose chatbots like ChatGPT (Abu-Shanab et al., 2023; Prasad & Dey, 2024; Saouabe et al., 2024) or HR virtual assistants (Khan et al., 2024). Consequently, the distinct impact mechanisms of varied generative models remain a conceptual "black box". To decode these mechanisms, we adopted the tripartite interpretive framework of Sun and Bunchapattanasakda (2019). Individual drivers encompass a sense of value (Cajander et al., 2026; Wu et al., 2025), empowerment (Alzeiby et al., 2025, Arora & Damarla, 2025), and psychological safety (Aulia & Lin, 2025; Dutta & Mishra, 2021). Job-level drivers feature task enrichment (Trinh et al., 2025), smart feedback (Aulia & Lin, 2025), and autonomy (Estherita & Vasantha, 2024). Finally, organizational drivers highlight integrated communication (Khan et al., 2024), supportive culture (Dutta et al., 2023; Marikyan et al., 2022), responsive leadership (Dutta & Mishra, 2025; Rane, 2023), and collaborative growth (Kuznetsov et al., 2024). Crucially, our synthesis exposes GenAI as a double-edged sword (Liu & Cheng, 2025; Liu & Li, 2025). The technology simultaneously empowers employees and triggers profound psychological stress. Figure 2 visualizes the thematic word cloud mapping these conflicting facilitating pathways and inhibiting pathways. Finally, to translate these impacts into behavioral outcomes, the extracted themes were embedded into an interpretive framework, categorizing the underlying mechanisms into individual, job, and organizational drivers. Consequently, the resulting model is a robust, evidence-based synthesis that captures the paradoxical 'double-edged' nature of GenAI, explicitly mapping 7 enabling pathways that elevate employee engagement against 6 inhibitory pathways that degrade it.

Although some of the identified facilitating pathways like task automation have also been discussed in previous studies on AI, the findings of this study indicated that the impact of GenAI on employee engagement is not solely driven by automation. The distinctive capabilities of GenAI, including the generation of new content, natural language-based interaction, human-like text generation, support for novel idea creation, and facilitation of knowledge access, create new pathways for employee learning, creativity, empowerment, and participation that go beyond the analytical and predictive functions of traditional AI (Mayer, 2025). A summary of the source analysis is presented in Figure 3.

**Figure 2.**
**The Word Cloud of Codes Forming Facilitating Pathways and Inhibiting Pathways in MAXQDA Software**




**(Source: The Researcher's Findings)**

## Positive Effects of GenAI on Employee Engagement

### Supporting the Employee's Mental Health and Well-being

GenAI tools foster psychological safety and compassionate communication, encouraging employees to engage in self-disclosure and facilitating empathetic interactions that promote daily emotional support (Dutta et al., 2023; Dutta & Mishra, 2025). Through periodic health assessments, self-evaluation, and monitoring mechanisms, they enable timely access to mental health resources and counseling support (Banerjee et al., 2024; Kadao & Balkrishna, 2025; Watanabe et al., 2025). Furthermore, by offering educational content and awareness initiatives on mental health, they holistically address the employees' cognitive, social, and fundamental quality-of-work-life needs (Dutta & Mishra, 2021, 2025; Watanabe et al., 2025; Wu et al., 2025).

### Smart Organizational Communication and Personalized Interaction

GenAI technologies serve as valuable enablers of organizational communication by providing 24/7 accessibility and HR self-service options that allow instant and continuous responses to inquiries, onboarding processes, and complex issues (Estherita & Vasantha, 2024; Kadao & Balkrishna, 2025; Kumar et al., 2025; Rane, 2023; Srivastava & Pandita, 2024). Through the generation of human-like text, conversational tone, and even humorous exchanges, these systems enhance perceived social presence while delivering highly customized recommendations, insights, and responses that create a personalized employee experience (Dutta et al., 2023; Dutta & Mishra, 2025; Hourani, 2025; Kumar et al., 2025; Srinivas, 2025). Interactive surveys and direct "employee voice" mechanisms promote two-way communication and real-time feedback, thereby strengthening the employee's voice and the exchange relationship between leadership and employees (Arora & Damarla, 2025; Aulia & Lin, 2025; Dutta & Mishra, 2021,2023; Khan et al., 2024; Rane, 2023).

**Advanced Analytics and Intelligent Monitoring of Engagement**

GenAI enables real-time tracking of emotional trends and employee engagement by collecting and analyzing feedback—both anonymous and explicit—using sentiment and emotion analysis (Abu-Shanab et al., 2023; Arora & Damarla, 2025; Hourani, 2025; Kadao & Balkrishna, 2025; Rane, 2023; Saouabe et al., 2024; Srinivas, 2025). Predictive analytics based on well-being indicators assist in the early identification of critical pain points, communication breakdowns, and potential risks such as turnover or burnout (Dutta & Mishra, 2021; Kumar et al., 2025; Lenka & Chanda, 2024; Saouabe et al., 2024). Leveraging HR analytics and instant, personalized insights, organizations can implement proactive HR interventions and tailor engagement strategies accordingly (Estherita & Vasantha, 2024; Saouabe et al., 2024).

**Intelligent Learning and Skill Development**

GenAI–powered tools personalize learning and development through adaptive learning models and customized training programs, creating unique learning experiences for each employee (Alzeiby et al., 2025; Arora & Damarla, 2025; Estherita & Vasantha, 2024; Khan et al., 2024; Srivastava & Pandita, 2024). . By accurately assessing and identifying individual skill gaps, they rapidly determine development priorities for targeted training (Alzeiby et al., 2025; Khan et al., 2024). Continuous improvement suggestions—delivered via AI-driven coaching and mentoring programs—position GenAI as a capable guide for professional growth (Kumar et al., 2025; Watanabe et al., 2025). By offering realistic simulations and easy access to educational resources, these systems foster self-directed and continuous learning, leading to skill enhancement and ongoing performance improvement (Arora & Damarla, 2025; Cajander et al., 2026; Paigude et al., 2023; Wu et al., 2025).

**Gamification, Recognition, and Smart Reward Management**

GenAI leverages gamification mechanisms to establish constructive competition and boost employee motivation through personalized rewards (Arora & Damarla, 2025). Continuous and precise performance feedback supports the targeted recognition of employees' daily efforts and accomplishments (Alzeiby et al., 2025; Kuznetsov et al., 2024; Srivastava & Pandita, 2024 ). Moreover, by mitigating biases in evaluation processes, AI-enabled systems ensure fair and accurate assessments through behavioral and performance analytics (Arora & Damarla, 2025; Dutta & Mishra, 2021; Estherita & Vasantha, 2024).

**Integrated Knowledge Management and Dynamic Content Generation**

GenAI technologies contribute to knowledge creation and content generation by producing deep insights and tailored information aligned with employee needs (Arora & Damarla, 2025; Kumar et al., 2025; Lenka & Chanda, 2024). Functioning as a centralized knowledge hub, they provide on-demand, real-time access to relevant information, facilitating knowledge sharing and retention across the organization (Kadao & Balkrishna, 2025; Kaur & Kaur, 2022; Khan et al., 2024; Kumar et al., 2025; Paigude et al., 2023). Acting as intelligent translators, they simplify complex information and generate AI-supported decision reports, thereby improving comprehension and decision-making processes among employees (Estherita & Vasantha, 2024; Kumar et al., 2025).

**Workflow Automation and Task Augmentation**

Through human–AI collaboration and task augmentation, employees can concentrate on higher-value responsibilities and develop innovative solutions for their organizations (Abu-Shanab et al., 2023; Aulia & Lin, 2025; Dutta & Mishra, 2021; Kadao & Balkrishna, 2025; Marikyan et al., 2022; Wu et al., 2025). By automating routine and repetitive tasks—such as task list management and survey distribution—these systems streamline operations and administrative workflows, reducing the workload of HR departments and minimizing repetitive manual efforts (Cajander et al., 2026; Kadao & Balkrishna, 2025; Kumar et al., 2025; Kuznetsov et al., 2024; Paigude et al., 2023; Rane, 2023; Srivastava & Pandita, 2024; Trinh et al., 2025). Additionally, by breaking down organizational silos and optimizing resource management, GenAI fosters informational integration and provides rapid solutions to workflow challenges (Dutta & Mishra, 2021; Khan et al., 2024; Prasad & De, 2024).

### Negative Effects of GenAI on Employee Engagement

**Job Insecurity and Fear of Replacement**

One of the most prominent inhibiting pathways associated with the use of GenAI is the emergence of perceived job threat and job insecurity. Employees may fear that automation and algorithmic decision-making will lead to job displacement, reduced opportunities for advancement, and even unemployment. Such concerns can diminish motivation, weaken organizational commitment, and ultimately reduce employee engagement (Estherita & Vasantha, 2024; Khan et al., 2024; Prasad & De, 2024; Rane, 2023).

**Technostress and Cognitive Overload**

Rather than facilitating work, GenAI may create technostress when organizational readiness and system design are inadequate. Information overload, system complexity, pressure for continuous learning, and algorithm-based monitoring can intensify stress, anxiety, and burnout. This condition directly depletes the employees' psychological energy and undermines engagement (Aulia & Lin, 2025; Prasad & De, 2024).

**Erosion of Human Interaction and Emotional Alienation**

Excessive reliance on GenAI systems—particularly chatbots and automated processes—may reduce meaningful human interaction in the workplace. Employees may feel that they are neither truly "seen" nor "understood", as machine-mediated communication begins to substitute for authentic interpersonal relationships. This emotional alienation can weaken the employees' sense of belonging and psychological connection to the organization, thereby lowering engagement (Arora & Demerla, 2025; Cajander et al., 2026; Dutta et al., 2023; Prasad & De, 2024).

**Ethical Concerns, Privacy Issues, and Distrust**

Concerns regarding data privacy, information security, opaque use of employee data, and the lack of algorithmic explainability constitute another major source of reduced engagement. Algorithmic bias and discriminatory decisions rooted in historical data can reinforce perceptions of injustice and erode the employees' trust in the organization and its HR systems. The resulting distrust can diminish both participation and engagement (Arora & Demerla, 2025; Hourani, 2024; Kadao & Balakrishna, 2025; Srivasta & Pandita, 2024).

**Reduced Autonomy and Diminished Meaning of Work**

Excessive use of GenAI, particularly in performance management and decision-making, may threaten the employees' sense of control, autonomy, and dignity at work. The automation of meaningful tasks and the delivery of impersonal algorithmic feedback may create the perception that employees are replaceable or undervalued. By negatively affecting self-esteem and meaning at work, this threat constitutes a key pathway through which engagement declines (Estherita & Vasantha, 2024; Rane, 2023; Srivastava & Pandita, 2024)

**Resistance, Pessimism, and Negative Reactions to Technology**

In response to the ambiguity, threat, and pressure associated with GenAI, employees may exhibit resistance, pessimism, or even refusal to use the technology. These negative reactions can be amplified when organizations fail to take tangible actions following the employee feedback or impose the technology without employee involvement. Such an environment may reduce participation and contribute to declining engagement (Banerjee et al., 2024; Kaur & Kaur, 2022; Marikyan et al., 2022, Prasad & De, 2024).

## Empirical Study Using BWM

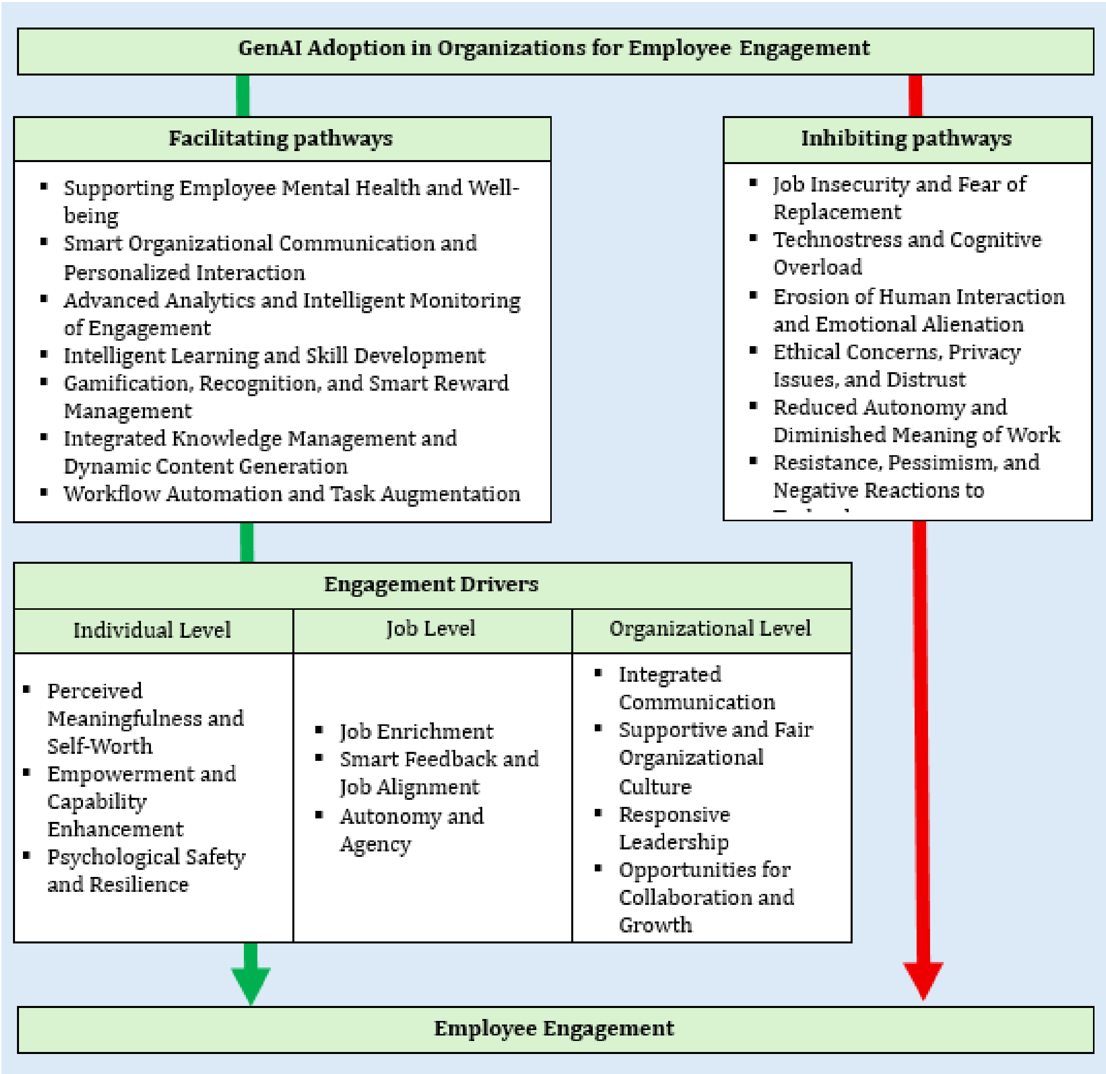
GenAI represents a dual-edged phenomenon in the domain of employee engagement, as it can simultaneously generate organizational value and introduce new risks. Given the emerging nature of this research area, the empirical phase of the study was designed to assign weights to, and prioritize, the identified facilitating pathways and inhibiting pathways. This step aimed to translate the theoretical framework into a more operational and decision-oriented level.

### Implementation Process and Results of the Empirical Study

The SLR identified two clusters of criteria: seven engagement facilitating pathways and six engagement inhibiting pathways associated with using GenAI at individual, job, and organizational levels. In the questionnaire, experts were asked to select, within each cluster, the most important and the least important criterion in terms of their impact on employee engagement. Subsequently, the relative importance of the "best" criterion over all other criteria, as well as the relative importance of all criteria over the "worst" criterion, was assessed using a scale from 1 to 9.

Given the variation in expert judgments regarding the best and worst criteria, the optimal weights of the facilitating pathways and inhibiting pathways, together with the inconsistency ratio for each expert, were calculated separately using LINGO software. The average values were then reported as the final results, as presented in Tables 4 and 5. The low inconsistency ratios—0.037 for the facilitating pathways and 0.017 for the inhibiting pathways—indicate the logical consistency and reliability of expert judgments (Rezaei, 2015).

**Figure 3.**
**The Impact of GenAI on Employee Engagement**




**(Source: The Researcher's Findings)**

## The Analysis of the Results of the Empirical Study

Table 4 shows that, among the seven facilitating pathways examined, integrated knowledge management and dynamic content generation emerged as the most important facilitating pathways of GenAI for enhancing the employee engagement, with a mean weight of 0.26, followed by workflow automation and task augmentation with a mean weight of 0.22. The next priorities were intelligent learning and skill development (0.14), smart organizational communication and personalized interaction (0.10), and advanced analytics and engagement monitoring (0.10). By contrast, supporting mental health and well-being and gamification, recognition, and smart reward management received the lowest weights.

Overall, this pattern indicated that experts from Iranian organizations place greater emphasis on operational and knowledge-oriented facilitating pathways of GenAI, particularly those that directly improve work quality, access to knowledge, and task efficiency, rather than on symbolic or well-being-oriented mechanisms such as gamification and mental health support. At the same time, this finding revealed a notable discrepancy between the prominence of certain themes in the literature and the priorities of experts. While previous studies, especially at the conceptual level, have emphasized the potential of GenAI to enhance the employee well-being, support mental health, and create interactive experiences through gamification, the participating experts considered these factors to be less important than more tangible and immediate benefits related to productivity, knowledge management, and performance improvement. Consistent with Wittenberg (2024), who emphasized the context-dependent nature of engagement, this difference may be attributed to the contextual conditions of organizations, their level of digital maturity, resource constraints, and managers' stronger focus on the operational and short-term outcomes of technology. Therefore, the results suggested that the importance of different GenAI facilitating pathways depends not only on their theoretical potential but also on the needs, priorities, and organizational conditions of each specific context.

**Table 4.**
**Ranking the Importance of GenAI Facilitating Pathways for Enhancing the Employee Engagement**

| Engagement-Enhancing Facilitating Pathways | Expert 1 | Expert 2 | Expert 3 | Expert 1 | Expert 2 | Expert 6 | Expert 7 | Expert 8 | Average | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| Workflow Automation and Task Augmentation | 0.168 | 0.257 | 0.160 | 0.166 | 0.313 | 0.153 | 0.387 | 0.233 | 0.229 | 2 |
| Intelligent Learning and Skill Development | 0.190 | 0.096 | 0.135 | 0.110 | 0.149 | 0.045 | 0.148 | 0.273 | 0.143 | 3 |
| Integrated Knowledge Management and Dynamic Content Generation | 0.347 | 0.289 | 0.298 | 0.294 | 0.176 | 0.436 | 0.111 | 0.156 | 0.261 | 1 |
| Smart Organizational Communication and Personalized Interaction | 0.076 | 0.144 | 0.106 | 0.166 | 0.117 | 0.091 | 0.074 | 0.104 | 0.109 | 4 |
| Supporting the Employee Mental Health and Well-being | 0.044 | 0.057 | 0.048 | 0.083 | 0.054 | 0.065 | 0.041 | 0.078 | 0.058 | 7 |
| Gamification, Recognition, and Smart Reward Management | 0.095 | 0.040 | 0.160 | 0.047 | 0.117 | 0.091 | 0.148 | 0.048 | 0.072 | 6 |
| Advanced Analytics and Intelligent Monitoring of Engagement | 0.076 | 0.112 | 0.106 | 0.130 | 0.070 | 0.114 | 0.089 | 0.104 | 0.100 | 5 |

**(Source: The Researcher's Findings)**

Table 5 indicates that, among the six principal inhibiting pathways, ethical concerns, privacy issues, and distrust ranked decisively first, with a mean weight of 0.56, making it the most serious threat to employee engagement. This finding suggested that ethical ambiguity, unclear data practices, and perceived violations of fairness can substantially undermine organizational trust and psychological safety, both of which are foundational to sustainable engagement. The second-ranked item was technostress and cognitive overload (0.17), indicating that the cognitive and emotional demands associated with GenAI may erode the employees' energy and work involvement when not properly managed.

A noteworthy point is the substantially higher weight assigned to ethical and privacy concerns compared with challenges such as job insecurity and technostress. This finding suggested that experts perceive ethical and privacy issues as a fundamental concern for the acceptance and effective use of GenAI (Golda et al., 2024). Unlike job insecurity and technostress, which mainly have individual-level consequences, risks related to data confidentiality, transparency, and accountability can affect the employees' trust and the legitimacy of using this technology at the organizational level. Moreover, this prioritization may reflect the organizations' greater sensitivity to data governance and regulatory requirements in digitally transitioning environments.

Job insecurity and fear of replacement ranked third, with a mean weight of 0.14. Although important, it was perceived as less influential than ethical concerns and technology-related strain. Erosion of human interaction and emotional alienation (0.08) and resistance, pessimism, and negative reactions to technology (0.07) received lower weights, suggesting that experts may view these outcomes as more contingent on implementation or more manageable in practice. The lowest weight was assigned to reduced autonomy, work dignity, and meaning of work (0.07), indicating that, under current conditions, identity- and meaning-related threats are perceived as less immediate than risks related to ethics, privacy, and trust.

**Table 5.**
**Ranking the Importance of GenAI Inhibiting Pathways in Undermining the Employee Engagement**

| Engagement Inhibitors | Expert 1 | Expert 2 | Expert 3 | Expert 4 | Expert 5 | Expert 6 | Expert 7 | Expert 8 | Average | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| Job Insecurity and Fear of Replacement | 0.090 | 0.130 | 0.114 | 0.116 | 0.156 | 0.190 | 0.162 | 0.191 | 0.143 | 3 |
| Technostress and Cognitive Overload | 0.090 | 0.093 | 0.190 | 0.193 | 0.186 | 0.198 | 0.121 | 0.365 | 0.179 | 2 |
| Erosion of Human Interaction and Emotional Alienation | 0.082 | 0.064 | 0.071 | 0.083 | 0.049 | 0.074 | 0.097 | 0.149 | 0.083 | 4 |
| Ethical Concerns, Privacy Issues, and Distrust | 0.648 | 0.617 | 0.562 | 0.549 | 0.500 | 0.492 | 0.440 | 0.143 | 0.562 | 1 |
| Reduced Autonomy and Diminished Meaning of Work | 0.090 | 0.093 | 0.061 | 0.057 | 0.107 | 0.043 | 0.121 | 0.041 | 0.076 | 6 |
| Resistance, Pessimism, and Negative Reactions to Technology | 0.073 | 0.093 | 0.069 | 0.083 | 0.079 | 0.077 | 0.056 | 0.107 | 0.079 | 5 |

**(Source: The Researcher's Findings)**

## Discussion and Conclusion

Using a combined approach of SLR and BWM, this study examined the dual role of GenAI in shaping the employee engagement. The findings showed that GenAI can function as both an enabler and a detractor of engagement. Employee engagement, therefore, is not an automatic outcome of technology adoption; rather, it emerges from the interaction between GenAI capabilities, employee perceptions, and the organizational context.

### Theoretical Implications

This study offers several exploratory theoretical contributions to the literature on employee engagement and digital transformation. First, it suggests that classical organizational behavior theories retain substantial explanatory power for understanding the emerging technological phenomena, even as the field of GenAI is still in an early stage of development. The effects of GenAI on employee engagement can be interpreted through the combined lenses of Kahn's engagement theory (Kahn, 1990), SET (Eisenberger et al., 1986), and the JD-R model (Bakker & Demerouti, 2007). From this perspective, GenAI is not merely a productivity tool; it represents a novel mechanism for reconfiguring psychological and job resources by enhancing meaningfulness, psychological availability, and psychological safety, strengthening perceived justice and organizational support, reducing energy-depleting demands, and expanding motivational resources such as autonomy and adaptive learning.

Although identified as an individual-level driver of employee engagement, psychological safety also appears to function as an underlying mechanism through which GenAI influences engagement. While learning opportunities, personalized support, and enhanced communication may strengthen the employees' sense of safety and confidence, concerns related to privacy, ethics, and job insecurity may undermine it. This finding reinforces Kahn's (1990) argument that psychological safety constitutes a fundamental condition for sustaining the employee engagement in technology-enabled workplaces.

Second, the findings underscore the context-dependent and inherently ambivalent nature of GenAI, highlighting the need to move beyond linear and overly optimistic accounts toward a contingency-based perspective. Consistent with recent studies (e.g., Asim & Ding, 2025; Radic et al., 2025; Xiao et al., 2025), GenAI is neither inherently a resource nor inherently a demand; its impact on engagement depends on system design, implementation quality, organizational culture, and employee perceptions.

By assigning the highest weight to ethical concerns, privacy issues, and distrust in the Best–Worst analysis, this study further suggests that ethics and trust should be treated as foundational boundary conditions within technology acceptance frameworks such as TAM and UTAUT (Choung et al., 2023; Marimon et al., 2025). Ignoring these dimensions may reverse the positive dynamics predicted by SET through a breach of the psychological contract. The main gap in the literature, therefore, is not whether GenAI has positive or negative effects, but under what conditions it activates motivational or strain-inducing pathways within the JD-R framework.

Third, by distinguishing and integrating the individual level (e.g., meaning and satisfaction), job level (e.g., autonomy and feedback), and organizational level (e.g., perceived organizational support), this study contributes to the literature on engagement drivers (Sun & Bunchapattanasakda, 2019). The findings confirm that employee engagement is a multidimensional and dynamic construct, and that GenAI adoption, as a socio-cognitive infrastructure, should be analyzed within a sociotechnical systems perspective, where technical infrastructures (algorithms) and social infrastructures (user psychology and organizational culture) are optimized in parallel and in alignment (Banh & Strobel, 2023).

Overall, by advancing an integrative, multilevel, and contingency-based account of how GenAI shapes the employee engagement, this study provides a foundation for developing testable causal models in future research and serves as an initial, context-specific starting point rather than a broadly generalizable framework. As one of the earliest studies in Iran to examine this relationship, it may also serve as a starting point for the expansion of context-sensitive research aimed at helping organizations in comparable developing economies sustain and enhance employee engagement in the digital era.

### Practical and Managerial Implications

The expert prioritization results obtained through the BWM provide a highly actionable roadmap for organizational leaders and HR managers navigating the sociotechnical integration of GenAI. To effectively manage the dual nature of this technology (Stahl et al., 2025) and improve operational execution**,** managers can move beyond conceptual technology adoption by considering the following strategic interventions:

First, because ethical concerns, privacy issues, and distrust received the highest weights, a foundational step involves the establishment of a formal AI Governance Framework. Organizational leaders and HR departments are encouraged to collaborate with IT to implement strict, documented data protection protocols. Furthermore, establishing an internal AI oversight committee tasked with conducting regular "algorithmic audits" can help ensure explainability and fairness in sensitive HR processes such as performance evaluation and engagement monitoring.

Second, to capitalize on integrated knowledge management and workflow automation, HR professionals can proactively redesign job descriptions. Instead of merely conceptualizing GenAI as a cognitive assistant, managers would benefit from launching structured AI onboarding programs that explicitly map out how routine tasks are delegated to AI. Leaders are advised to deploy AI-driven knowledge hubs—equipped with automated summarization and data analysis capabilities—and facilitate practical workshops on "prompt engineering" to help employees actively redirect their cognitive resources toward innovation and complex problem-solving (Abu-Shanab et al., 2023; Bader & Kaiser, 2019; Khan et al., 2024; Striukova & Vasantha, 2024).

Third, to directly mitigate the challenges of technostress and job insecurity, management is recommended to adopt a phased change management strategy. Avoiding abrupt technological deployments, leaders can introduce GenAI tools through targeted pilot programs and incremental rollouts. HR departments could establish dual-support systems including technical upskilling bootcamps coupled with accessible psychological counseling programs to maintain psychological safety and prevent cognitive overload.

Fourth, organizations can operationalize personalized learning by deploying GenAI-powered Learning Management Systems (LMS). HR managers have the opportunity to utilize these platforms to conduct real-time skills gap analyses and automatically generate customized micro-learning pathways tailored to individual employees' learning styles, directly reinforcing their competence and engagement.

Fifth, while GenAI can optimize emotional analytics and personalized communication (Kumar et al., 2025), HR executives are encouraged to institutionalize a "human-in-the-loop" communication policy. Operational guidelines can specify that AI-generated performance or emotional insights serve strictly as supplementary data. Core relational practices—such as periodic face-to-face performance appraisals, empathetic leadership dialogues, and mentoring—are best kept as human-led activities to preserve authentic organizational connections.

Finally, to ensure the sustainable adoption in developing economies including Iran—where baseline employee engagement requires structural reinforcement—executives would benefit from adopting a human-centered digital strategy backed by targeted resource allocation. Strategic HR planning could include dedicated budgets for developing hybrid capabilities, specifically supporting the simultaneous training of AI literacy, analytical thinking, and socio-cognitive skills. This targeted investment helps ensure employees evolve into capable partners in a complementary human-AI ecosystem, preventing passive technological dependence.

### Limitations and Directions for Future Research

First, the empirical phase of the study, which aimed to weight and prioritize the facilitating pathways and inhibiting pathways of GenAI, relied on the opinions of eight experts from three Iranian organizations. Although the low inconsistency ratio indicated an acceptable level of reliability in the judgments, the limited sample size and the study's reliance on subjective evaluations restricted the generalizability of the findings.

Moreover, while the conceptual framework was derived from a systematic review of international studies, the prioritization of factors was conducted within the Iranian organizational context. Therefore, the resulting weights and rankings should be interpreted in light of similar cultural, economic, and institutional conditions. Accordingly, validating this framework across different countries and industries could help assess the stability and generalizability of the findings. In addition, similar to the findings of Rožman and Tominc (2024), experts' demographic characteristics including gender may have influenced the results.

Second, since the study was based on SLR and thematic analysis, its findings depend on the quality, scope, and potential biases of previous studies. Methodological heterogeneity, differences in organizational contexts, and the possibility of publication bias may have affected the comprehensiveness of the results.

Third, given the emerging nature of GenAI, a considerable portion of the available evidence remains exploratory and cross-sectional, while in-depth longitudinal and empirical studies in this field are still limited. Moreover, the exceptionally rapid pace of publication in the GenAI field makes it challenging for literature reviews to remain fully up to date.

Fourth, the dominant focus of the literature on chatbots and LLM has limited our understanding of other types of generative technologies and different levels of system.

Accordingly, future research could employ larger samples, cross-country studies, and longitudinal designs to examine more precisely the role of contextual factors and the mechanisms through which GenAI affects the employees’ work engagement. Several directions for future research emerge from these limitations. First, longitudinal and multilevel studies are needed to examine how GenAI affects the employee engagement, well-being, burnout, and performance over time. Second, future studies should empirically test causal models that incorporate mediating and moderating factors such as trust, psychological safety, self-efficacy, perceived justice, leadership style, and organizational culture. Third, finer distinctions among generative technologies, application domains (e.g., HR, operations, and knowledge-intensive services), and job characteristics may help identify contingency patterns and contextual differences. Fourth, more systematic investigations of adverse outcomes—including algorithmic bias, cognitive dependence, skill degradation, privacy concerns, and ethical tensions—are necessary to develop a balanced and realistic understanding of GenAI in organizations. Fifth, cross-cultural and cross-sector research can clarify how cultural, institutional, and industrial conditions shape both perceptions and impacts of GenAI.

Ultimately, advancing this domain requires a strategic shift from descriptive summaries toward rigorous, context-sensitive causal research that robustly explains the nuanced integration of GenAI within the modern workforce.

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