

AI and Humans: Integrating Technology and Competence for Enhanced Sales Enablement

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Sales enablement (SE) has become a critical business imperative, yet academic research remains limited. Drawing on information processing theory and the job demands-resources model, this study examines the integration of technology and coaching—two core SE tools—in a sales call center. It proposes that combining Generative Artificial Intelligence (GenAI) with structured human coaching, rather than relying exclusively on either, can reduce stress arising from algorithm aversion and information overload, lower turnover intentions, enhance sales performance, and improve organizational outcomes and employee well-being. The study advances theory by redefining SE as a construct in which technology can function as both a job resource and a demand, integrating information processing theory with the job demands-resources model to address its limitations, challenging the brain-as-computer analogy by incorporating stress responses, and redefining AI as a dynamic resource that, when paired with human oversight, extends beyond rigid automation and substitution for human judgment. It also offers managerial guidance on change management, coaching, data governance, scalable IT integration, and interdepartmental collaboration.

Keywords: GenAI, sales enablement, algorithm aversion, information overload, sales performance, information processing theory, job demands-resources model

INTRODUCTION

With increasingly dynamic and competitive markets where organizations are continually pursuing performance optimization, SE has emerged as a critical business imperative (Toman et al., 2017). In 2013, only 19% of companies had a dedicated enablement person, program, or function, a figure that increased to 59% by 2017 (Matthews & Schenk, 2018). More recently, Seismic (2023) reported that 71% of respondents indicated their companies planned to increase enablement investments, while Gartner (2022) noted that over 50% of CSOs expected enablement to extend beyond sales to support marketing and customer success. SE has also led to a rapidly growing industry of service providers that focus on serving Fortune 500 companies (Westbrook & Peterson, 2020). Despite its growing practical importance, academic research on SE remains limited, especially regarding the roles of technology and coaching that constitute the core components of SE along with onboarding, training, marketing content and strategy, and sales operations, all of which are integral to a unified strategic framework (Peterson et al., 2021). Although researchers have studied technology and coaching (in the SE context) in parallel (Bolander et al., 2020; Jelinek et al., 2006; Magnotta et al., 2020; Montecchi et al., 2022; Plangger et al., 2020; Speier & Venkatesh, 2002), current research on SE reveals a notable gap in understanding how these core components can be effectively integrated, which is crucial for determining the extent to which their combined application can enhance

sales performance compared to their individual contributions. This paper aims to resolve this gap by integrating the two components.

Drawing on the information processing theory (Miller, 1956) and the job demands-resources model (Demerouti et al., 2001), this study integrates technology and coaching in the context of a sales call center, wherein it proposes that combining advanced technologies like GenAI with traditional structured human coaching methods, rather than relying exclusively on one, can reduce stress and turnover intentions while enhancing sales performance, ultimately leading to improved organizational outcomes and employee well-being. The context of a sales call center was chosen for several reasons. Research indicates that investments to the scale of more than \$1 trillion are made by companies towards call centers (that handle over 265 billion customer calls per year) and toward coaching agents to enhance the quality of services (Luo et al., 2021). This huge investment is a testimony of how important it is to coach call center agents so that quality improves, sales increase, and the bottom line is strengthened. However, sales call center environments are inherently highly stressful (de Ruyter et al., 2001) often leading agents to engage in job hopping (Patten, 2016). A study indicates that nearly half (47%) of the employees intend to quit their jobs within a year and a half (EvalAgent, 2023). If a sales call center were to rely exclusively on either advanced technology (GenAI) or coaching by human supervisors, it could inadvertently intensify existing job stressors. This heightened stress might lead to increased turnover intentions, which in turn would drive up the costs of recruiting new agents (Kemp et al., 2025). The resulting cycle of continuous departures and rehiring could ultimately erode the call center's profits. Another reason for choosing a sales call center as the context of this study was that these centers operate in complex, digital environments where merging technology with human expertise can enhance efficiency, customer satisfaction, responsiveness, and innovation (Singh et al., 2024). Leveraging GenAI to streamline coaching can reduce inefficiencies and free supervisors for strategic initiatives (Isguzar et al., 2024; Laskar et al., 2023; Luo et al., 2021; Reinhard et al., 2024). Also, striking a balance between automation and human-centric approaches can be the key to mitigating resistance, ensuring technology supports essential human judgment, and promoting employee well-being and long-term success (Kaaria, 2024; Parasuraman & Wickens, 2008; Valtonen & Kimpimäki, 2023) in sales call centers—an industry that accounts for a market size of £2.5 billion (Jones, 2023)).

This study makes several key contributions to literature. It bridges a critical gap by unifying the previously separate SE domains of technology and coaching, presenting a novel hybrid feedback model that combines GenAI-generated insights with traditional human coaching to overcome the limitations of each approach alone. By synthesizing information processing theory with the job demands-resources model, the research demonstrates how integrating technology and human coaching can alleviate information overload (Eppler & Mengis, 2004), reduce algorithm aversion (Jussupow et al., 2020), and lower turnover intentions among sales call center agents. In doing so, it redefines job resources to encompass advanced AI tools when paired with human oversight, thereby broadening the theoretical discourse on AI-human collaboration in high-pressure sales environments and expanding the job demands-resources model to include AI-augmented work settings. Moreover, the study shows that this hybrid model can enhance performance evaluation and employee well-being, while also offering practical managerial strategies for change management, training, data governance, scalable IT integration, and interdepartmental collaboration.

LITERATURE REVIEW

Peterson and Dover (2020) define SE as a “cross-functional assimilation (marketing, training operations, management, automation, etc.) of content, processes, and technology that readies a firm to more productively assist the customer’s journey” (p. 46) whereas as Peterson et al. (2021) characterize it as a comprehensive, dynamic capability that harmonizes diverse firm resources to enhance the customer journey and improve selling productivity. The same authors (Peterson et al. (2021)) explain it as a broad construct that includes onboarding, training, marketing content and strategy, sales operations, coaching, and technology, all of which can be considered integral components of a unified strategic framework. In fact, Rangarajan et al. (2020) highlight that SE is instrumental in integrating these diverse elements into a

cohesive business strategy. Further, Friend et al. (2024, p. 2) define SE strategy as “a firmwide strategy that directs internal and external resources, integrates firm culture, and establishes operations that empower the sales function to capitalize on the firm’s core capabilities.” Research also indicates that SE can enhance key sales outcomes, such as performance and supplier relationships, while also diminishing less favorable workplace effects (Friend et al., 2024). For instance, Westbrook and Peterson (2020) viewed SE as a valuable job resource that strengthens salespeople’s capabilities. Despite its growing practical importance, with as many as 85% of firms reporting SE initiatives (Peterson & Dover, 2021), academic research on SE remains limited, especially regarding the roles of technology and coaching.

Encouragingly, a body of literature has begun to examine the technological dimensions of SE wherein it has been characterized as a facilitator of sales performance by automating key processes, diversifying knowledge transfer, and streamlining sales operations (Montecchi et al., 2022; Plangger et al., 2020). Moreover, studies on technology adoption in the context of SE reveal a more detailed picture. While initial technology rollouts tend to receive favorable perceptions, long-term adoption often suffers due to issues such as misalignment between system functionalities and sales force needs (Jelinek et al., 2006; Speier & Venkatesh, 2002). The technology acceptance model (Davis, 1989) highlights the importance of perceived usefulness and ease-of-use in driving adoption (Schillewaert et al., 2005), yet research indicates that the effectiveness of SE technologies is contingent upon supportive organizational contexts such as management commitment and cross-functional integration (Cascio et al., 2010; Weinstein & Mullins, 2012). This gap calls for further investigation into how SE technologies can be optimally integrated within dynamic sales environments, particularly in light of disruptive advancements like artificial intelligence (Singh et al., 2019).

Parallel to the technological dimension, the coaching aspects of SE are critical for translating technological investments into tangible sales performance improvements. Scholars have emphasized the importance of continuous learning and development in ensuring that sales personnel can effectively leverage SE initiatives (Bolander et al., 2020; Magnotta et al., 2020). Organizational learning theories advocate for coaching mechanisms that align with long-term business goals and individual skill development (Garvin, 1993; Hallikainen et al., 2020). Sales supervisors play a pivotal role in this regard by providing ongoing, personalized coaching to reinforce learning and facilitate effective application in the field (Badrinarayanan et al., 2015; Lupton et al., 1999).

Building on these insights, sales researchers have recognized for some time the significance of sales coaching in assisting new salespeople in adjusting to their work environment, providing them with the necessary knowledge, skills, and abilities, promoting desirable behaviors, and correcting dysfunctional patterns through effective interventions (Mallin, 2018). As per Corcoran et al. (1995), sales coaching refers to a series of conversations and activities aimed at offering continuous feedback and support to salespersons or sales team members to enhance their performance and increase revenue generation (Peasley, 2022). Although supervisors and salespeople may have different perspectives related to sales coaching (Nguyen et al., 2022) and research has identified several positive outcomes associated with it, including enhanced salesperson motivation, reduced role ambiguity, increased job satisfaction, improved satisfaction with supervisors, and elevated job performance (Badovick et al., 1992; Onyemah, 2009). Comer & Drollinger (1999) propose that supervisors can employ sales coaching to facilitate the development of active, empathetic listening skills among salespeople. This ability enables them to effectively interpret both verbal and nonverbal cues from clients during sales interactions, responding appropriately with matching verbal and nonverbal communication (Comer & Drollinger, 1999). Moreover, sales supervisors can utilize a coaching approach to support salespeople prone to experiencing anxiety by helping them acknowledge, anticipate, and cope with sales call anxiety, thereby reducing any associated stigmatization (Kemp et al., 2013; Verbeke & Bagozzi, 2000). Consequently, coaching by supervisors can influence the attributions and behavioral intentions of inexperienced salespeople following unsuccessful sales calls (Badovick et al., 1992; Dixon et al., 2003).

With the advent of AI, sales coaching can now be performed by an AI coach without direct supervisor intervention (Khandelwal & Upadhyay, 2021; Luo et al., 2021) wherein AI coaches deliver real-time, customized, and round-the-clock coaching. In sales, poor customer service can have deleterious

consequences on firm performance: more than 66% of customers deflect from companies that fail to provide adequate access to services and information (Timm, 2008), and each year, poor customer service leads to companies losing over \$75 billion in revenues (Teich, 2019). Consequently, companies invest significant resources to enhance their customer service processes through in-house agents or call centers (Luo et al., 2021). This substantial investment underscores the crucial role of coaching sales call center agents in enhancing service quality, increasing sales, and strengthening the bottom line (Liu & Batt, 2010; Tilka & Johnson, 2018). The use of an AI coach in a sales call center setting helps analyze agent conversations and provide targeted feedback to improve job performance, leveraging deep learning algorithms and cognitive speech analytics (Luo et al., 2021). For example, MetLife has reaped immense benefits by adopting an AI coach to offer training feedback to its call center agents (Council, 2019), and Zoom has leveraged its AI coach, Chorus, to provide on-the-job training for its sales team (Matheny, 2019).

In recent years, GenAI has transformed coaching in sales call centers by automating and streamlining the feedback process for agents (Laskar et al., 2023; Luo et al., 2021). By harnessing large language models and deep learning algorithms, GenAI systems evaluate both live and recorded interactions to pinpoint key performance metrics, such as tone, clarity, and responsiveness (Sundar et al., 2024; Xia et al., 2024). Utilizing cognitive speech analytics, these systems capture subtle linguistic and emotional cues, providing immediate, personalized feedback on communication effectiveness (Perera et al., 2024). This real-time, data-driven approach highlights areas in need of improvement such as overcoming hesitant responses or enhancing customer engagement and delivers actionable recommendations that agents can quickly implement (Mummar et al., 2024). Furthermore, GenAI continually refines its feedback processes by learning from vast amounts of historical and real-time data, ensuring that its insights remain contextually relevant and precise (Herb & Lloyd, 2024; Lee & Moore, 2024; Patel et al., 2024). This adaptive learning enables the AI to manage a wide range of customer interactions and keep pace with evolving market demands, ensuring that sales call center agents remain agile and well-prepared (Reinhard et al., 2024; Yan et al., 2024). By shouldering the varied aspects of coaching, GenAI alleviates the traditional workload on supervisors, allowing them to focus on broader strategic priorities while the AI offers consistent, 24/7 support (Laskar et al., 2023; Luo et al., 2021; Reinhard et al., 2024). As a result, organizations benefit from enhanced service quality and operational efficiency, ultimately driving better sales performance (Reinhard et al., 2024; Singh et al., 2024).

Yet, current research on SE reveals a significant gap in understanding how its two critical components—technology and coaching—can be integrated, specifically in terms of how advanced technologies like GenAI can be combined with traditional structured human coaching methods (instead of using either of the two exclusively) to reduce stress and turnover intentions and enhance sales performance, thereby positively impacting overall organizational outcomes and employee well-being. Although Luo et al. (2021) recommend using an AI coach–human coach assemblage for optimal results in coaching sales call center agents, their study does not address the broader benefits of such a combination, particularly regarding the reduction of turnover intentions and the achievement of strategic gains. In modern sales call centers where SE is vital for coordinating resources and enhancing the customer journey (Peterson & Dover, 2020), it is essential to explore how these technologies can alleviate job stressors thereby reducing turnover intentions and building a healthier, more engaged workforce. Moreover, closing this gap matters for several reasons. First, sales call centers operate in increasingly stressful, complex, and digital environments (Shin et al., 2015), where effective integration of technology and human expertise can lead to significant competitive advantages such as enhanced operational efficiency, improved customer satisfaction, faster responsiveness to market changes, and increased innovation (Singh et al., 2024). Second, by harnessing GenAI effectively, call centers can streamline coaching processes, reducing inefficiencies and allowing supervisors to focus on strategic initiatives that strengthen organizational performance (Isguzar et al., 2024; Laskar et al., 2023; Luo et al., 2021; Reinhard et al., 2024). Third, understanding how to balance technological automation with human-centric approaches is critical to mitigating negative perceptions and resistance, ensuring that technology complements rather than replaces essential human judgment, and thereby contributes to improved employee well-being and long-term organizational success (Kaaria, 2024; Parasuraman & Wickens, 2008; Valtonen & Kimpimäki, 2023).

Further, responding to a call in literature to identify which measures predict the adoption and usefulness of SE technologies in people development (Friend et al., 2024), this research examines the key determinants of technology acceptance in sales environments. In particular, it investigates factors such as perceived usefulness, ease-of-use, and the effective integration of GenAI with human coaching. Drawing on the information processing theory (Miller, 1956) and the job demands-resources model (Demerouti et al., 2001), the study examines how streamlined feedback, reduced job stressors and a balanced approach between automated insights and empathetic human oversight are crucial for the successful adoption and practical application of SE technologies.

PERFORMANCE FEEDBACK – EXCLUSIVELY VIA SALES CALL CENTER SUPERVISORS

Sales call center supervisors play a crucial role in monitoring and enhancing customer interactions by reviewing both live and recorded calls, analyzing an array of performance metrics, such as call duration, tone, resolution time, adherence to scripts, compliance, and customer satisfaction, and subsequently providing targeted, personalized feedback (Karakus & Aydin, 2016; Liu & Batt, 2010). Their responsibilities include identifying both strengths and areas for improvement among sales call center agents, often through individualized coaching sessions and team meetings (Liu & Batt, 2010). However, if the evaluative processes employed by them are not carefully structured, there could be certain repercussions (Hunter & Goebel, 2008). Given the high volume of calls managed daily, it can become challenging for supervisors to distinguish between good and bad calls; as a result, they may listen to numerous calls to ensure that a representative sample of poor interactions is captured (Karakus & Aydin, 2016; Kim, 2007; Park, 2011). On all these calls, supervisors must provide detailed feedback to agents (Karakus & Aydin, 2016; Liu & Batt, 2010), resulting in the delivery of more information than the agents can process effectively, a phenomenon defined in the literature as information overload (Eppler & Mengis, 2004). Also, the use of numerous performance indicators, while designed to capture every detail of an agent's performance, can blur the relative importance of each metric (Cheng et al., 2007; Pritchard et al., 2007). This can often result in conflicting priorities that compel agents to expend significant cognitive resources to reconcile feedback from multiple channels such as emails, dashboards, and meetings (Westover, 2024). The resulting information overload can not only increase stress levels but also contribute to turnover intentions, as agents overwhelmed by constant adjustments and ambiguous guidance may feel undervalued and incapable of meeting shifting expectations (Klauegger et al., 2007; Misra & Stokols, 2012; Noor & Maad, 2009).

PERFORMANCE FEEDBACK – EXCLUSIVELY VIA GenAI

GenAI represents an emerging technological advancement that harnesses sophisticated machine learning algorithms and natural language processing to synthesize large volumes of data into concise, actionable insights (Grewal et al., 2024). By processing quantitative information from various data sources, GenAI can distill complex performance metrics into clear summaries and provide tailored recommendations, functioning effectively as a diagnostic tool (Silva et al., 2025). Conversely, while GenAI offers significant benefits by assessing all calls handled by a sales call center on a daily basis, thereby allowing supervisors to focus more effectively on team management and overall productivity (Isguzar et al., 2024), relying solely on automated systems for performance evaluation introduces its own challenges (Dwivedi et al., 2024; Yan et al., 2024). One critical issue is algorithm aversion, where agents develop skepticism or reluctance to trust recommendations produced exclusively by an automated system (Dietvorst et al., 2015; Turel & Kalhan, 2023). When sales call center agents receive feedback that is purely mechanistic and devoid of contextual subtlety or empathy, they may question its fairness and accuracy (Clark et al., 2013; Steelman & Rutkowski, 2004). This perception of impersonal, 'black box' outputs can lead to heightened stress and diminish engagement with the feedback process, ultimately exacerbating turnover intentions as agents feel alienated from the decision-making process (Plooy & Roodt, 2010; Walsh et al., 1985).

PERFORMANCE FEEDBACK – SALES CALL CENTER SUPERVISORS AND GenAI IN TANDEM

The limitations inherent in the two approaches underscore the need for an integrated model that combines the analytical efficiency of GenAI with the detailed, empathetic oversight provided by experienced call center supervisors. In such a hybrid framework, GenAI can augment the evaluation process by effectively distinguishing between routine and problematic calls and filtering out interactions that adhere to established protocols (Reinhard et al., 2024). This targeted approach can enable supervisors to concentrate exclusively on calls requiring intervention or coaching, saving significant time and enhancing overall productivity (Liu & Batt, 2010). Moreover, GenAI serves as a powerful SE tool that rapidly processes and aggregates data, thereby eliminating extraneous details while highlighting critical performance indicators (Laskar et al., 2023; Luo et al., 2021; Mummar et al., 2024). This diagnostic capability can reduce the volume of redundant information that sales call center agents must parse and streamline the feedback process, allowing supervisors to focus on providing contextually rich and actionable guidance (Lee & Moore, 2024; Sterne & Davenport, 2024). In doing so, supervisors can be better positioned to interpret the data within the unique context of individual interactions, thereby ensuring that the feedback is both comprehensive and comprehensible (Huang & Rust, 2024; Jain et al., 2024).

Moreover, integrating GenAI with human oversight may directly address the issue of algorithm aversion. When sales call center agents see that automated insights are not being imposed in isolation but are instead reviewed and supplemented by a knowledgeable supervisor, they shall be more inclined to trust and engage with the feedback (Cancro et al., 2022; Hoff & Bashir, 2015; Liu & Batt, 2010; de Visser et al., 2012). The human element, characterized by empathy, contextual judgment, and personalized coaching, can help demystify the opaque nature of AI-generated recommendations (Srivastava & Feigh, 2024; Terblanche et al., 2022; Zhang et al., 2024). This collaborative process can transform what might otherwise be perceived as cold, impersonal data into meaningful insights that account for the subtleties of real-world interactions. As supervisors validate and refine the recommendations produced by GenAI, agents can receive feedback that is not only data-driven but also sensitive to the complexities of human communication, reducing feelings of disempowerment and isolation (Westphal et al., 2023; Yan et al., 2024).

Furthermore, the joint application of GenAI and call center supervisors may contribute to a more coherent communication process. GenAI is capable of aggregating information from diverse sources into unified, digestible reports, which supervisors can then contextualize based on their firsthand observations and understanding of team dynamics (Han et al., 2024; Mummar et al., 2024; Pimentel & Veliz, 2024). This consolidation can mitigate the fragmentation and redundancy that often occur when feedback is delivered through multiple channels, thereby minimizing information overload (Luo et al., 2021). With clearer, more focused guidance, sales call center agents can better prioritize their efforts, reducing the stress associated with trying to interpret an overwhelming array of metrics (Kennedy & Pretorius, 2008; Mellor et al., 2015). Over time, this approach can not only foster improved performance but also contributes to higher job satisfaction and lower turnover rates, as agents feel supported and equipped to meet their performance goals (Connell & Harvey, 2004; Futrell & Parasuraman, 1984; Leblanc, 2013; Zito et al., 2018).

In summary, while call center supervisors (Karakus & Aydin, 2016; Liu & Batt, 2010) and GenAI (Grewal et al., 2024; Silva et al., 2025) each offer distinct advantages in performance evaluation, relying exclusively on one approach can lead to significant drawbacks, either in the form of information overload and increased stress from overly detailed human feedback (Hunter & Goebel, 2008; Klausegger et al., 2007; Misra & Stokols, 2012; Noor & Maad, 2009) or algorithm aversion resulting from impersonal, automated outputs (Dietvorst et al., 2015; Turel & Kalhan, 2023). The integrated model can leverage the diagnostic power of GenAI to process and streamline data (Laskar et al., 2023; Luo et al., 2021; Mummar et al., 2024) while capitalizing on the supervisor's ability to provide empathetic, context-rich feedback (Lee & Moore, 2024; Sterne & Davenport, 2024; Huang & Rust, 2024; Jain et al., 2024). This balanced strategy can not only alleviate information overload (Kennedy & Pretorius, 2008; Mellor et al., 2015) and mitigate algorithm aversion (Cancro et al., 2022; Hoff & Bashir, 2015; Liu & Batt, 2010; de Visser et al., 2012) but also serve

as a robust SE resource that lowers work stressors and ultimately reduces turnover intentions among sales call center agents (Connell & Harvey, 2004; Futrell & Parasuraman, 1984; Leblanc, 2013; Zito et al., 2018). Please see Table 1 for a summary of selected literature.

TABLE 1
SELECTED LITERATURE

Author(s)	Topic/Construct	Key findings/Contribution
Westbrook & Peterson, 2020	Sales Enablement	SE initiatives lower burnout and turnover rates while improving sales performance.
Peterson & Dover, 2020	Sales Enablement	Presents SE framework of technology, content, and people that bridges the customer journey and traditional selling.
Peterson & Dover, 2021	Sales Enablement	Finds that while SE initiatives mainly target salespeople and account managers, other regional stakeholders are involved, and SE services differ significantly across regions.
Peterson et al., 2021	Sales Enablement	Characterizes SE as a multidimensional construct and multi-stage process model encompassing sales support diagnostics, sales capital reconfiguration, enablement infrastructure rollout, enablement performance evaluation, and enablement calibration.
Friend et al., 2024	Sales Enablement	Develops a typology of SE strategy.
Onyemah, 2009	Sales Coaching	Sales coaching is associated with positive outcomes such as increased affective commitment, improved job and supervisor satisfaction, and reduced role ambiguity.
Shin et al., 2015	Stress	Stress leads to increased call center employee turnover intentions.
Demerouti et al., 2001	Job Demands-Resources Model	Introduces the job demands-resources model of burnout.
Miller, 1956	Information Processing Theory	Examines limits on the capacity of humans to process information.
Eppler & Mengis, 2004	Information Overload	Reviews theory and definitions of information overload, including its causes, effects, and countermeasures. Finds that information overload leads to stress.
Grewal et al., 2024	GenAI	Introduces a four-quadrant framework outlining trade-offs between the type of GenAI inputs and the degree of human augmentation required for its outputs.
de Ruyter et al., 2001	Call Centers	Examines role stress antecedents and consequences in a call center environment.
Liu & Batt, 2010	Call Center Supervisors	Supervisors contribute to performance improvements through increased coaching and group incentives.
Jussupow et al., 2020	Algorithm Aversion	Presents factors influencing algorithm aversion.

Note: A table showing selected literature that is most relevant to this study. SE = Sales Enablement.

THEORETICAL BACKGROUND

Information Processing Theory (Miller, 1956) offers a framework for understanding how individuals capture, process, store, and retrieve information by likening the human mind to a computer that receives stimuli through various senses, processes this input, and stores it in memory for later use. However, as Mayer (1996) points out, this analogy fails to account for the psychological responses that are inherent to human cognition—responses such as stress, which play a critical role in shaping behavior. In sales call center environments, supervisors provide continuous and multifaceted feedback on performance metrics such as call duration, tone, resolution time, adherence to scripts, compliance, and customer satisfaction (Karakus & Aydin, 2016; Liu & Batt, 2010). Although such detailed feedback is intended to capture the full intricacy of an agent's performance, the sheer volume and fragmented presentation of this information can exceed the limited cognitive capacity of sales call center agents leading to information overload (Cheng et al., 2007; Pritchard et al., 2007; Westover, 2024), if feedback is provided exclusively by sales call center supervisors. Eppler & Mengis (2004) define information overload as receiving more information than one can process effectively, a state that Jackson and Farzaneh (2012) further describe as hindering an individual's ability to extract the necessary knowledge from the data. This means that when agents are inundated with unfiltered and excessively granular feedback on a high number of calls, often delivered via emails, dashboards, and meetings, they expend substantial cognitive effort trying to reconcile conflicting priorities (Hunter & Goebel, 2008; Westover, 2024). Over time, this persistent overload not only increases work-related stress (Eppler & Mengis, 2004; Stanley & Clipsham, 1997) but also contributes to higher turnover intentions (Shin et al., 2015).

Proposition 1: *When performance feedback is provided exclusively by call center supervisors, the extensive and fragmented presentation of multiple performance metrics on an overwhelming number of calls can lead to higher levels of information overload among sales call center agents. This information overload, in turn, can increase work-related stress and ultimately contribute to elevated turnover intentions.*

GenAI functions as an efficient data processor, distilling vast amounts of information into concise, actionable insights (Grewal et al., 2024; Silva et al., 2025). However, unlike human supervisors who engage in psychological responsiveness, interpreting both the cognitive and emotional dimensions of communication, purely algorithmic systems lack this empathetic processing. This absence means that when performance evaluation relies solely on GenAI, the system's mechanistic output fails to provide the contextual intricacy and emotional support needed for effective information interpretation. As a result, agents may experience algorithm aversion—a reluctance to trust or act on algorithm-generated recommendations (Dietvorst et al., 2015; Jussupow et al., 2020; Turel & Kalhan, 2023). The additional processing required to decipher ambiguous feedback can heighten stress and, ultimately, contribute to higher turnover rates (Plooy & Roodt, 2010; Walsh et al., 1985).

Proposition 2: *When performance feedback is delivered solely through GenAI, the impersonal and mechanistic nature of the automated feedback can give rise to algorithm aversion among sales call center agents. This aversion can heighten work-related stress and, consequently, increase turnover intentions.*

While the information processing theory effectively explains why both information overload and algorithm aversion occur, by highlighting the limitations in human cognitive processing and the absence of psychological responsiveness in purely algorithmic systems (Eppler & Mengis, 2004; Jussupow et al., 2020), it does not, in itself, offer a remedy for these issues. A solution is offered by the job demands-resources model (Demerouti et al., 2001), a complementary framework that distinguishes between job demands (stressors) and job resources (the supports that can buffer such demands). Within the context of call centers, the reliance on solely human supervisors or GenAI can create unbalanced job demands. When supervisors provide all feedback, the sheer volume of unfiltered data can overwhelm agents, whereas exclusive reliance on GenAI can lead to algorithm aversion due to the absence of empathetic, contextual

guidance. The job demands-resources model posits that the adverse effect of such high job demands can be mitigated by adequate job resources. In this context, integrating GenAI with experienced call center supervisors emerges as a critical job resource. Here, GenAI can function as an efficient diagnostic tool that aggregates and distills performance data, filtering out redundant and extraneous details (Silva et al., 2025). Simultaneously, call center supervisors can provide essential contextual insights, empathetic support, and personalized coaching (Lee & Moore, 2024; Sterne & Davenport, 2024; Huang & Rust, 2024; Jain et al., 2024). This collaborative approach can not only alleviate information overload (Kennedy & Pretorius, 2008; Mellor et al., 2015) and mitigate algorithm aversion but also reduce overall work stress and lower turnover intentions (Connell & Harvey, 2004; Futrell & Parasuraman, 1984; Leblanc, 2013; Zito et al., 2018).

Proposition 3: *An integrated performance feedback system that combines GenAI's ability to distill and aggregate performance data with the contextual, empathetic guidance of human supervisors can reduce both information overload and algorithm aversion among sales call center agents. This reduction can lower work-related stress and decrease turnover intentions.*

Thus, while the information processing theory elucidates the cognitive limitations that lead to information overload and algorithm aversion, it does not inherently prescribe solutions. The job demands-resources model, by emphasizing the importance of balancing high job demands with sufficient job resources, offers a remedial strategy. The integration of GenAI with human supervision exemplifies this balance, creating a more supportive and efficient feedback system that can enhance performance and well-being among sales call center agents. This synthesis of the information processing theory and job demands-resources model not only advances the theoretical understanding of the challenges associated with performance evaluation in high-pressure sales environments but also provides a viable pathway for reducing work-related stress and turnover.

The theoretical propositions are now operationalized into the following testable hypotheses (Kanaparan & Strode, 2021), which can be empirically tested in a study conducted within a sales call center environment. Such an investigation holds the potential to assess the impact of both supervisor feedback and GenAI-generated feedback on sales call center agents' experiences of information overload, algorithm aversion, stress, and turnover intentions.

H₁: *Performance feedback exclusively provided by sales call center supervisors results in information overload among sales call center agents.*

H₂: *Information overload among sales call center agents results in them experiencing stress.*

H₃: *Performance feedback exclusively provided by GenAI results in algorithm aversion among sales call center agents.*

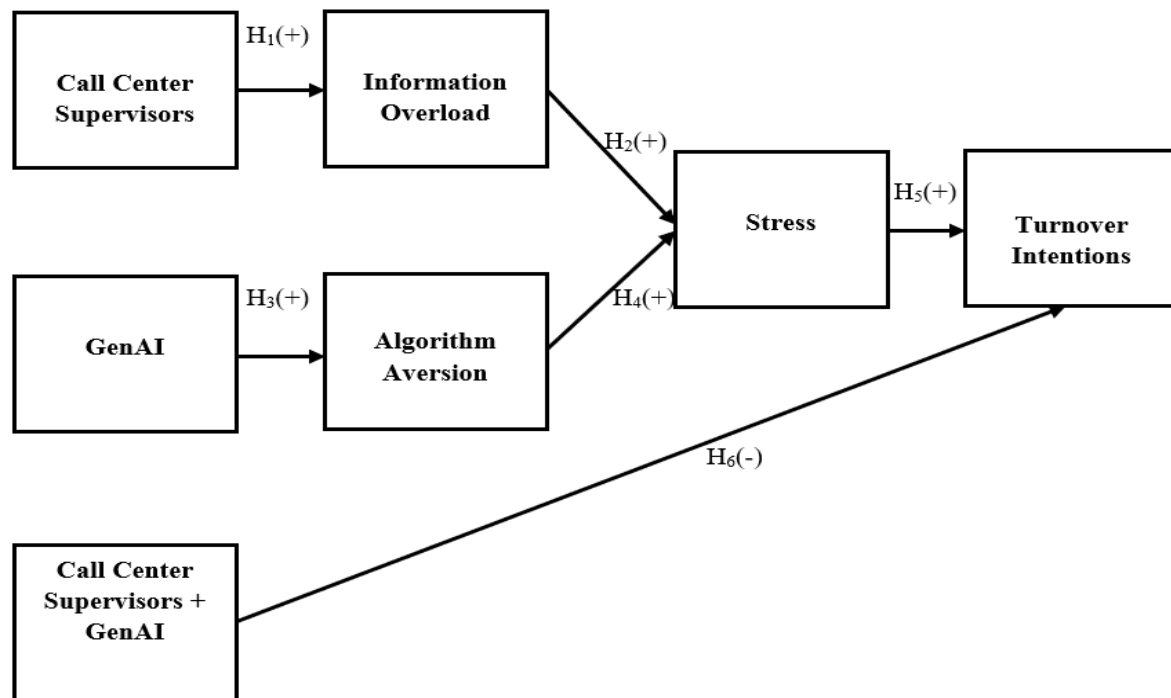
H₄: *Algorithm aversion among sales call center agents results in them experiencing stress.*

H₅: *Stress experienced by sales call center agents results in their increased intentions to quit.*

H₆: *Performance feedback provided by a combination of sales call center supervisors and GenAI results in reduced intentions to quit among sales call center agents.*

Please see Figure 1 for the conceptual model.

FIGURE 1
CONCEPTUAL MODEL



Note: A conceptual model illustrating how performance feedback from both supervisors and GenAI affects sales call center agents' experiences of information overload, algorithm aversion, stress, and turnover intentions.

DISCUSSION

SE aims to streamline the sales process and improve performance by synchronizing people, processes, and technology (Friend et al., 2024). It is an expansive construct that encompasses onboarding, training, marketing content and strategy, sales operations, coaching, and technology, all serving as essential elements of a cohesive strategic framework (Peterson et al., 2021). Although it is recognized as one of a firm's highest priorities—with 59% of organizations having invested in dedicated enablement roles, programs, or functions (Matthews & Schenk, 2018)—academic research on SE remains limited, particularly regarding the roles of technology and coaching, which have been examined separately in literature (Bolander et al., 2020; Jelinek et al., 2006; Magnotta et al., 2020; Montecchi et al., 2022; Plangger et al., 2020; Speier & Venkatesh, 2002).

Research into SE technologies has found that they boost sales performance by automating processes, diversifying knowledge transfer, and streamlining operations (Montecchi et al., 2022; Plangger et al., 2020). However, while initial rollouts are often positively received, long-term adoption can falter due to misalignment between system functionalities and sales force needs (Jelinek et al., 2006; Speier & Venkatesh, 2002). The technology acceptance model underscores that perceived usefulness and ease-of-use drive adoption (Davis, 1989; Schillewaert et al., 2005), yet supportive organizational contexts, such as management commitment and cross-functional integration, are also critical (Cascio et al., 2010; Weinstein & Mullins, 2012).

Whereas research on coaching has demonstrated that they are essential for converting technology investments into improved sales performance, as continuous learning and personalized coaching enhance both individual skills and organizational outcomes (Bolander et al., 2020; Garvin, 1993; Hallikainen et al., 2020; Magnotta et al., 2020). Sales coaching, whether by supervisors or through AI, helps new and existing salespeople adjust, improve communication, and reduce anxiety, leading to better performance and job

satisfaction (Badovick et al., 1992; Badrinarayanan et al., 2015; Comer & Drollinger, 1999; Kemp et al., 2013; Lupton et al., 1999; Onyemah, 2009; Verbeke & Bagozzi, 2000). With advancements in AI, coaching is increasingly automated; GenAI systems now leverage deep learning and cognitive speech analytics to deliver real-time, personalized feedback that continually adapts through learning from both historical and live data (Khandelwal & Upadhyay, 2021; Laskar et al., 2023; Luo et al., 2021; Perera et al., 2024; Sundar et al., 2024; Xia et al., 2024). This 24/7 AI support reduces the burden on human supervisors while enhancing service quality and overall sales performance (Herb & Lloyd, 2024; Lee & Moore, 2024; Patel et al., 2024; Reinhard et al., 2024; Singh et al., 2024).

Yet, current research on SE reveals a notable gap in understanding how these two essential components—technology and coaching—can be effectively integrated. This paper aims to resolve this gap by integrating the two components. Specifically, this study proposes the combination of advanced technologies like GenAI with traditional structured human coaching methods to provide performance feedback to sales call center agents. Rather than relying solely on one approach, which can lead to algorithm aversion (Jussupow et al., 2020) or information overload (Eppler & Mengis, 2004), ultimately increasing stress, turnover intentions, and negatively affecting organizational outcomes, this study advocates a combined strategy. While GenAI efficiently processes performance data to deliver actionable insights (Laskar et al., 2023; Luo et al., 2021; Mummar et al., 2024; Silva et al., 2025), its advantages can be maximized when complemented by personalized coaching from experienced supervisors (Laskar et al., 2023; Liu & Batt, 2010; Luo et al., 2021). In essence, the proposed hybrid model leverages GenAI to enhance, rather than replace, human coaching, thereby creating a more supportive work environment that mitigates stress and turnover intentions. Figure 2 (see Appendix) demonstrates how arguments have been transformed into visual representations that make the premises and conclusions of this study more transparent and facilitate a more precise assessment of their validity.

Theoretical Implications

This study contributes to theory in several ways. First, it informs the information processing theory (Miller, 1956) well by confirming certain predictions that it makes. The theory is based on the idea that humans do not merely respond to stimuli from the environment. Instead, humans process the information that they receive, which is stored in their memory and retrieved as and when required. This study offers a theoretical contribution by challenging one of the assumptions of the theory that compares the functioning of the brain to that of a computer, capable of processing and analyzing environmental information. The assumption, however, disregards the inability of computers to experience psychological responses compared to the immense influence of such responses on human behavior. One such response that this study explores is the stress experienced by sales call center agents (Shin et al., 2015). This stress can be attributed either to increased information overload (Eppler & Mengis, 2004) from feedback provided by sales call center supervisors or to algorithm aversion (Jussupow et al., 2020) resulting from GenAI feedback, both of which can lead to higher turnover intentions among sales call center agents (Shin et al., 2015). This negative impact of relying solely on one feedback source supports the study's argument against the exclusive implementation of either feedback mechanism.

Second, although literature has viewed SE as a valuable job resource that augments salespeople's capabilities (Westbrook & Peterson, 2020), this positive framing may not universally apply to all components of the SE strategic framework. In particular, the technological component—as exemplified in this study by the exclusive use of GenAI for feedback—can inadvertently transform SE into a job demand wherein if GenAI is used as the sole source of providing feedback to sales call center agents can lead to algorithm aversion. Accordingly, SE should not be considered only a job resource; it must also be viewed as a potential job demand. This theoretical contribution cautions researchers and practitioners to critically evaluate technology's role within SE, ensuring that its implementation does not impose additional demands before it is widely adopted in sales environments.

Third, this study emphasizes the limitations of the information processing theory in addressing challenges such as information overload and algorithm aversion. While the information processing theory effectively explains how cognitive limitations and the lack of psychological responsiveness in algorithmic

systems contribute to these issues, it does not offer a framework for resolving them. To fill this gap, this study integrates the information processing theory with the job demands-resources model (Demerouti et al., 2001), which provides a complementary perspective by distinguishing between job demands and job resources. Specifically, the information processing theory explains why job demands arise in the feedback process within sales call centers—either due to an overwhelming volume of unfiltered data when feedback is provided exclusively by human supervisors or due to algorithm aversion when feedback is entirely reliant on GenAI. However, the job demands-resources model offers a structured approach to resolving these challenges by balancing job demands with job resources. The integration of GenAI with human supervision serves as a key resource that reduces information overload (Kennedy & Pretorius, 2008; Mellor et al., 2015) and mitigates resistance to algorithmic feedback by incorporating contextual understanding, empathetic support, and personalized coaching (Lee & Moore, 2024; Sterne & Davenport, 2024; Huang & Rust, 2024; Jain et al., 2024). Thus, while the information processing theory identifies the problem, the job demands-resources model provides a remedy by highlighting the importance of balancing demands with resources. By synthesizing these two theoretical perspectives, this study makes a theoretical contribution by demonstrating how AI-human integration can serve as a viable solution to information-processing challenges in highly stressful sales environments.

Fourth, this study advances the job demands-resources model by redefining job resources to include technological components alongside traditional human, social, and organizational factors. While prior research has primarily conceptualized job resources as elements such as supervisor support, skill development, autonomy, and career growth (Bakker et al., 2010), this study positions AI as a novel, non-traditional job resource. When effectively integrated with human oversight, AI can help reduce information overload and mitigate algorithm aversion, offering a structured means of balancing job demands. By demonstrating that job resources can extend beyond human-driven mechanisms to include AI-driven solutions, this study broadens the job demands-resources model's applicability to AI-augmented work environments.

Fifth, this study reinterprets algorithm aversion through the lens of the job demands-resources model. While prior research typically attributes resistance to AI-driven decision-making to issues of trust and a lack of control (Dietvorst et al., 2015; Turel & Kalhan, 2023; Jussupow et al., 2020), this study stipulates that algorithm aversion can also stem from an imbalance between job demands and available resources. In essence, the workplace effectiveness of AI depends on its role as a complementary job resource integrated with human oversight, rather than as an isolated decision-making tool. By embedding AI within a balanced system that merges human judgment with AI-driven analytics, organizations can alleviate the adverse effects associated with algorithm aversion.

Sixth, prior research has largely focused on AI's role in task automation, often portraying it as either a substitute for human judgment or a fixed system governed by pre-programmed decision-making rules (Agrawal et al., 2018; Lubars & Tan, 2019; Strich et al., 2021). In contrast, this study stresses AI's adaptability when integrated with human supervision, emphasizing that its effectiveness as a job resource is contingent on contextual integration rather than mere deployment. Specifically, AI can reduce information overload by synthesizing and filtering information (Silva et al., 2025), while human supervisors provide the necessary psychological sensitivity and contextual interpretation to ensure meaningful feedback (Srivastava & Feigh, 2024; Terblanche et al., 2022; Zhang et al., 2024). By redefining AI as a dynamic, co-evolving job resource, this study advances the theoretical discourse on AI-human collaboration, particularly within high-pressure sales environments.

Lastly, current research on SE reveals a significant gap in understanding how to integrate its two essential components, i.e., technology and coaching. This study advances the SE literature by introducing a hybrid feedback model that addresses critical shortcomings in existing performance evaluation systems. It challenges the binary perspective of either AI (objective feedback) or human supervisors (subjective feedback) to provide feedback to sales call center agents by proposing a hybrid approach in which AI synthesizes and filters data to generate structured feedback (Silva et al., 2025), while human supervisors contextualize, interpret, and personalize these insights (Srivastava & Feigh, 2024; Terblanche et al., 2022; Zhang et al., 2024). This model not only enhances feedback precision but also ensures that agents receive

guidance that is both data-driven and empathetically delivered. By positioning this AI-human hybrid approach as a more effective alternative to conventional feedback mechanisms, this study offers a fresh theoretical perspective on optimizing performance evaluations in sales call centers.

Managerial Implications

This study offers clear managerial implications for sales call centers operating in increasingly complex, digital, and high-pressure environments (Shin et al., 2015). By blending advanced AI analytics with human expertise, the proposed framework delivers several strategic advantages. The deployment of GenAI systematically reviews every customer interaction, identifying deviations from performance standards (Reinhard et al., 2024). This targeted approach streamlines performance monitoring, enhances supervisor productivity, and allows them to concentrate on high-impact areas and strategic initiatives rather than routine oversight (Isguzar et al., 2024; Laskar et al., 2023; Luo et al., 2021; Reinhard et al., 2024). Consequently, coaching processes become more efficient, enabling quicker responses to market changes and improving overall agility (Şahin & Karayel, 2024).

Relying exclusively on human-driven feedback can overwhelm agents with too much information (Eppler & Mengis, 2004), while an AI-only approach may lack the refined judgment essential for effective guidance and might even trigger algorithm aversion (Dietvorst et al., 2015; Jussupow et al., 2020; Turel & Kalhan, 2023). By integrating GenAI's capacity to process and synthesize large datasets (Grewal et al., 2024; Silva et al., 2025) with the empathetic, context-rich insights of experienced supervisors (Laskar et al., 2023; Liu & Batt, 2010; Luo et al., 2021), the framework creates a dual-layered quality control system. This balanced method not only enhances the precision of performance feedback but also supports employee well-being and helps mitigate resistance to technological change (Kaaria, 2024; Parasuraman & Wickens, 2008; Valtonen & Kimpimäki, 2023), resulting in reduced turnover intentions and enhanced sales performance.

Integrating GenAI with human coaching creates an effective, cost-saving feedback system for call centers. GenAI quickly analyzes the high volume of daily customer interactions to generate data-driven insights and pinpoint key areas for improvement (Mummar et al., 2024). Simultaneously, human coaches add essential context, empathy, and tailored guidance (Laskar et al., 2023; Liu & Batt, 2010; Luo et al., 2021). This combination reduces the need for large in-house quality review teams, thereby cutting operational costs and allowing supervisors to focus on strategic training and coaching (Kahn et al., 2020; Luo et al., 2021). The result is a highly personalized and efficient feedback system that drives continuous improvement and strengthens overall performance.

Investing in state-of-the-art AI tools provides real-time, actionable insights that distinguish between routine and problematic interactions (Ananthiga K et al., 2024; Schmitt et al., 2008), optimizing resource allocation by reducing the manual review burden. Equally important is the development of supervisors, ensuring they are skilled in interpreting AI-generated data and translating it into effective coaching (Khandelwal & Upadhyay, 2021; Laskar et al., 2023), a dual investment that is essential for sustaining competitive advantage (Singh et al., 2024).

Successful implementation of this hybrid framework also depends on aligning organizational processes and ensuring collaboration among departments such as IT, sales, customer service, and human resources (Feng et al., 2024). Clear communication protocols help integrate the technological infrastructure with the human-centric aspects of the feedback system (Cascio et al., 2010; Weinstein & Mullins, 2012), reinforcing a culture that values both efficiency and empathetic leadership.

Also, managers should establish regular evaluation protocols using key performance indicators like agent stress levels, turnover intentions, customer satisfaction, and sales performance to monitor the system's impact. Continuous, data-driven assessments allow for ongoing refinement of the feedback mechanism, ensuring that it remains effective (Bassamboo & Zeevi, 2009).

Managers need to adopt comprehensive change management strategies to effectively handle the cultural and operational shifts that shall come with integrating AI analytics into traditional supervisory methods (Chhatre & Singh, 2024). By involving stakeholders early in the process and transparently communicating

the long-term benefits of a hybrid system, organizations can ease transitions and reduce resistance to change (Alhusban et al., 2024; Sterne & Davenport, 2024).

Given the reliance on extensive datasets and real-time analytics (Grewal et al., 2024; Silva et al., 2025), it is imperative to establish strict data governance and ethical standards (Eacersall et al., 2024; Zlotnikova et al., 2025). Also, policies that ensure data accuracy, security, and transparency mitigate risks of misuse and foster trust among employees and customers (Huynh, 2024; Xia et al., 2024). Furthermore, as organizations expand, it is essential to guarantee that AI systems integrate seamlessly with existing IT infrastructures and can scale to meet growing demands (Sagi, 2024; Wang et al., 2023). Strategic planning for system interoperability and regular updates will help preserve the effectiveness of the AI-human hybrid model even as operational complexities increase (Bansal et al., 2019; Gabriel et al., 2023).

Overall, blending advanced AI analytics with experienced human oversight not only refines performance monitoring and elevates feedback precision but also revolutionizes various organizational practices. Through the adoption of robust change management, investment in tailored coaching, enforcement of rigorous data governance, planning for scalable integration, and implementation of detailed performance evaluations, managers can build a resilient framework. This framework can boost efficiency, reduce operational costs, support employee well-being, and build a lasting competitive advantage for sales call centers.

LIMITATIONS, FUTURE RESEARCH DIRECTIONS, AND CONCLUSIONS

This study clearly states the underlying premises and assumptions of all arguments. The recommendations that it provides are explicitly expressed and align with the arguments, premises, and assumptions. However, like all research studies, it is not exempt from limitations. Following the guidelines of Kanaparan and Strode (2021), the study operationalizes its theoretical propositions into testable hypotheses but does not actually test them, resulting in a lack of empirical evidence. Future research could empirically test these hypotheses in a sales call center setting. Such a study would offer significant insights into how both supervisor-provided and GenAI-generated feedback affect agents' experiences of information overload, algorithm aversion, stress, and turnover intentions.

Moreover, the study's focus on sales call center environments may limit its applicability to other sales contexts or industries. Future research could overcome this limitation by empirically testing the proposed hybrid feedback model in diverse organizational settings and investigating potential moderating factors, such as the organization's overall technological readiness, its structure or industry-specific variables (Randolph et al., 1991; Tehrani et al., 1990), that might influence the effectiveness of integrating GenAI with human coaching. Additionally, factors like the frequency and quality of feedback, the nature of sales interactions (Polo & Sese, 2016), and the competence or leadership style of supervisors could also play moderating roles. Furthermore, longitudinal studies could provide valuable insights into the long-term impact (Bolander et al., 2017; Chintagunta & Labroo, 2020; Gao et al., 2021; Siau & Yang, 2017) of the hybrid model.

Another limitation is that the study overlooks the cost implications and resource requirements of implementing GenAI. This omission may affect the model's feasibility across various settings, given the diversity in organizations' financial resources and technological infrastructures. To remedy this, future research should incorporate a cost-benefit analysis that quantifies both the upfront investments, such as technology acquisition, system integration, and staff coaching, and the ongoing operational expenses (Miller & Bapat, 1999). Developing a decision framework that balances these costs against anticipated benefits, such as increased efficiency, lower turnover, and improved performance, would enable organizations to assess the economic viability of GenAI implementation.

Finally, research on the technology component of the SE strategy framework has characterized it as a facilitator of sales performance, noting its role in automating key processes, diversifying knowledge transfer, and streamlining sales operations (Montecchi et al., 2022; Plangger et al., 2020). Accordingly, in addition to integrating technology with coaching, future research could also examine how it might be

integrated with other components of the SE framework i.e., onboarding, training, marketing content and strategy, and sales operations.

In conclusion, current research on SE highlights a notable gap in understanding how its two components—technology and coaching—can be integrated effectively. This study bridges that gap by introducing a comprehensive hybrid feedback model that combines GenAI-generated insights with traditional human coaching. This integrated approach not only overcomes the shortcomings of relying exclusively on either technology or human input but also enriches theoretical discussions by merging information processing theory with the job demands-resources model. The study suggests that this balanced integration can significantly reduce information overload, lessen algorithm aversion, and decrease turnover intentions among sales call center agents, thereby boosting overall performance and employee well-being. Furthermore, this research expands the concept of job resources by incorporating advanced AI tools alongside human oversight, thereby extending the boundaries of AI-human collaboration in high-pressure sales settings. It also provides a practical roadmap for managers by outlining strategies in change management, customized coaching, robust data governance, scalable IT integration, and cross-functional collaboration. These managerial implications call on organizations to leverage technological innovations while preserving the critical, detailed support of human coaching. Ultimately, this study marks a transformative shift in SE—by merging the precision of GenAI with the empathetic insight of human coaching, the proposed hybrid model turns challenges like information overload and algorithm aversion into catalysts for superior performance, empowering organizations to achieve agile, data-driven decision-making paired with empathetic leadership and secure a sustainable competitive edge in today's ever-changing business environment.

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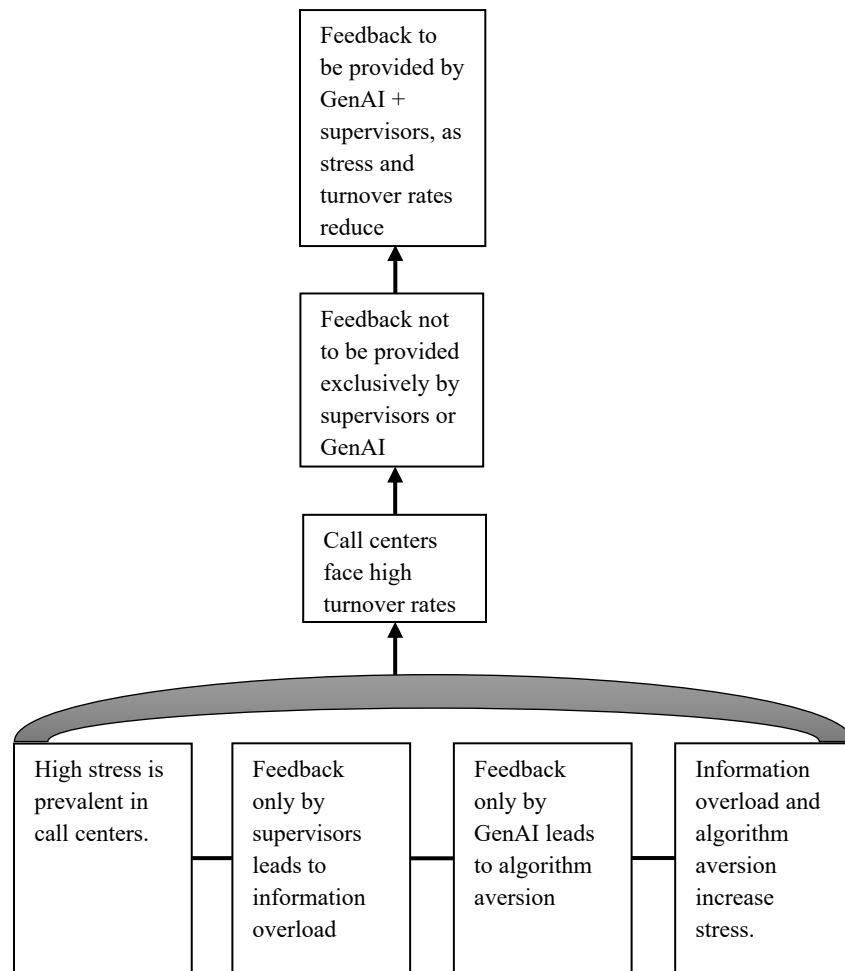
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APPENDIX

FIGURE 2
ARGUMENT DIAGRAM



Note: A visual depiction of premises, arguments, and conclusions related to the implementation of providing feedback via both sales call center supervisors and GenAI.