Machines vs. Humans: The Effect of Artificial Intelligence Feedback on Employee Behavior and Performance

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Abstract

The integration of (AI) into management control systems has transformed how organizations evaluate employee performance and deliver feedback. This study investigates the impact of AI-generated performance feedback on employee learning, emotional arousal, and job performance compared to human-generated feedback. Drawing on the Theory of Perception, we conducted an experimental study by employing an electrodermal activity (EDA) method, a physiological measure, to examine employees' responses to AI-driven versus human-driven feedback. The results indicate that employees exhibit higher learning under AI feedback than under human feedback. However, AI feedback elicits lower levels of positive emotional arousal compared to human feedback. Additionally, performance feedback provided by AI leads to higher employee performance than feedback from human managers. These findings contribute to the management accounting literature by offering empirical insights into AI adoption in performance evaluation and its implications for employee behavior and performance.

Key words: Artificial intelligence, performance feedback, electrodermal activity, human-driven feedback

1. Introduction

In today's technologically advanced and dynamic workplace, the incorporation of artificial intelligence (AI) has transformed various facets of management control systems (Chen et al., 2022; Jia et al., 2023; Luo et al., 2022; Tong et al., 2021). An emerging area of AI incorporation into management control systems involves conducting job evaluation procedures and delivering performance feedback to employees. Recently, many corporations like Alibaba, Amazon, IBM, and MetLife, have incorporated AI in their management control systems (Heaven, 2020; Luo et al., 2022; Roose, 2020). Specifically, AI employs advanced deep learning neural network algorithms and cognitive speech analytics to perform a managerial function overseeing employee performance and generating data-driven feedback to enhance employees' skills (Brynjolfsson et al., 2019; Jarrahi, 2018).

Compare to conventional management control systems, AI-driven management control systems are a sophisticated automated technological development that can effectively analyze both unstructured (such as audio, video, and text) and structured employee behavior data on a wide scale (Luo et al., 2022; Tong et al., 2021). This capability of AI allows for the detection of complex and hidden patterns of employee performance that may be difficult to uncover using conventional systems. Therefore, AI presents a distinct opportunity for organizations to create value and relieve managers from the repetitive tasks of delivering data-based performance feedback to train their employee. No wonder that business leaders and researchers are keen to comprehend the impact of AI integration into management control systems on employee behavior and performance.

However, there is intense debate within both literature and practice about replacing humans with AI in organizational management control systems (Agrawal et al., 2019; Dietvorst et al., 2015; Luo et al., 2022). Some scholars believe that the ability of AI to collect and analyze data for generating feedback surpasses that of humans (Fountaine et al., 2019; Tong et al., 2021). Others argue that human managers with transformational styles and higher interpersonal skills can communicate feedback information to employees more effectively (Fehrenbacher et al., 2018; Leicht-Deobald et al., 2019; Luo et al., 2022), which is better than the performance feedback effect of AI. Even if a machine has "hard" data analysis advantages, it cannot have the "soft" interpersonal communication ability that humans have (Luo et al., 2019). The research of Tong et al. (2021) show that the positive and negative effects of AI in providing employee performance feedback and found that the two effects coexist.

Employees' reactions to AI-generated feedback are shaped by their perception of AI as a feedback provider. *The Theory of Perception* (Gibson, 1979) explains that individuals interpret stimuli based on prior experiences, cognitive expectations, and contextual cues. While AI-driven feedback is objective and data-driven, employees may perceive it as impersonal due to AI's lack of emotional awareness and contextual understanding (Gray et al., 2007; Yam et al., 2021). This perception can lead to algorithmic aversion, with employees favoring human managers who provide more personalized and empathetic feedback (Dietvorst et al., 2015; Logg et al., 2019). Understanding this perceptual distinction is crucial, as it influences employees' emotional responses and confidence in AI feedback, ultimately shaping its effectiveness within management control systems.

Moreover, feedback provided by AI could be subject to debate due to their potential lack of subjective judgment capability, limited experience of emotions and physical sensations (e.g., pleasure, hunger, pain), and moderate agency in thinking, planning, and acting (Gray et al., 2007; Yam et al., 2021). Prior research in both psychology and accounting has consistently demonstrated that individuals exhibit algorithmic aversion and are hesitant to rely solely on algorithms, preferring human judgment (Dietvorst et al., 2015; Logg et al., 2019). However, firms have already started integrating AI as a replacement for conventional management control systems owing to its technological superiority. Therefore, the transition from humans to AI has ignited a growing interest in understanding the impact of AI feedback employee behavior and performance compared human feedback.

We aim to address this research gap. Drawing upon prior research on the distinctive technological advantages in data collection and analysis, as well as the capacity to provide precise and comprehensive predictions (Fountaine et al., 2019; Jarrahi, 2018; Tong et al., 2021), we argue that, compared to humans, the integration of AI for providing employee performance feedback enables a more consistent consideration of a substantial volume of data with heightened precision. Consequently, this augmentation in data processing fosters an enhanced employee learning under AI feedback compared to human feedback. On the other hand, feedback generated by AI could be subject to debate due to their potential lack of subjective judgment capability, limited experience of emotions and physical sensations (e.g., pleasure, hunger, pain), and moderate agency in thinking, planning, and acting, as suggested by previous studies (Gray et al., 2007; Yam et al., 2021), which may lead employees to hold negative perceptions towards AI-driven feedback. Based on employees' perception of AI as emotionless or low-experience, we argue that AI-generated feedback activates lower positive employees' emotional arousal than human feedback. Aligned with the existing literature, we posit that AI, as opposed to humans, operates based on specific, traceable, and transparent rules, resulting in more consistent and objective decisions, particularly in performance feedback. This, in turn, is likely to enhance employee confidence and overall performance.

We conducted a 2 × 2 between-subject experimental design to test our hypotheses. The two experimental factors were feedback source and feedback nature, and each experimental factor had two levels, with a total of four independent experimental groups. A total of 48 participants were randomly allocated to one of four experimental conditions and were directed to participate in a two-round symbol translation task. According to Dickhaut et al. (2010), physiological reactivity can offer a fundamental comprehension of accounting data. Previous study suggests that individuals' emotional arousal and heart rate, as a measure of learning, are physiological indicators of task-related reactivity (Caruelle et al., 2019; Darnell & Krieg, 2019; McCraty, 2015). Drawing inspiration from previous studies, we measured learning and emotional arousal via participants' physiological reactivity, notably using electrodermal activity (EDA), a skin-conducting device, to measure these aspects.

Our findings unveiled that AI-generated feedback, as opposed to human-generated feedback, led to higher levels of employee learning while simultaneously eliciting lower levels of positive emotional arousal, as evidenced by both EDA measurements and emotional facial expressions. Furthermore, our analysis indicated that employee performance exhibited improvements when feedback was generated by AI in compared to human-generated feedback. Importantly, the moderation analysis highlighted that employees' emotional arousal moderates the relationship between their performance and learning.

Our study contributes the existing management accounting literature by shedding light on the distinct effects of AI feedback on employee behavior and performance. It corroborates previous accounting research (Biswas et al., 2024; Commerford et al., 2022; Tong et al., 2021; Yalcin et al., 2022) by demonstrating that AI-generated feedback has distinctive effects compared to human-generated feedback. The findings are congruent with theoretical frameworks that highlight the potential of AI to provide consistent and data-driven feedback, resulting in enhanced employee learning and performance. This contributes to a greater comprehension of the relationship between technology, human behavior, and performance outcomes. Additionally, the incorporation of emotional facial expressions and physiological reactivity measures, such as EDA, provides a novel perspective for evaluating employee responses to AI feedback. This study also advances theoretical understanding by integrating the Theory of Perception to explain how employees interpret and respond to AI-generated feedback compared to human feedback. By demonstrating that AI feedback enhances learning and performance while eliciting lower emotional arousal, this research extends existing theories on feedback effectiveness and algorithmic aversion in management control systems. Moreover, this study offers practical implications for organizations considering AI integration into their performance evaluation processes, suggesting that AI-driven feedback systems can enhance employee development while acknowledging potential emotional drawbacks.

The study highlights the potential benefits for firms of integrating AI-generated feedback into performance management systems. AI can be considered a beneficial tool for enhancing employee learning and performance by firms. However, the study's finding of diminished positive emotional arousal in response to AI-generated feedback calls for careful implementation. Firms should consider strategies to balance the objective feedback of AI with personalized human interaction to meet the emotional requirements of their employees. In addition, the mediation analysis provides insight into the mechanism by which AI feedback influences performance, highlighting the significance of supporting a learning-oriented environment conducive to learning.

The findings of this study hold an implication for firms in terms of the potential return on investment that invest in AI-driven performance management systems. As evidenced by the research, AI-generated feedback positively impacts employee learning and, as a result, enhances their performance. This correlation between AI feedback and improved employee performance suggests that firms that invest strategically in AI technology for feedback delivery will likely experience a positive impact on their overall business performance. Thus, by y incorporating AI-driven performance management systems, firms can potentially attain increased employee performance, better task execution, and higher job satisfaction.

The study's findings highlight the prospective advantages of AI integration in performance management systems from a policy standpoint. Policymakers can promote the adoption of AI-powered feedback as a means to improve employee learning and performance. However, policies should also emphasize the significance of maintaining a human contact throughout the feedback process in order to address emotional aspects. In addition, policies can foster collaboration between technology developers and organizational psychologists to design AI systems that take into account both the cognitive and emotional dimensions of employee feedback.

This paper is structured as follows: Section 2 covers the theoretical background and hypotheses development, including the institutional setting, AI vs. human decision-making, and hypotheses. Section 3 details the methodology, including participants and manipulation, experimental equipment, task and procedure, and variable measurement. Section 4 presents results and discussion, covering the manipulation check and hypothesis testing. Section 5 concludes with key findings, limitations, and future research directions.

2. Theoretical Background and Hypotheses Development

2.1 Institutional Setting

Organizations are increasingly integrating AI-driven performance evaluation systems to enhance efficiency, reduce bias, and provide objective feedback to employees (Biswas et al., 2024; Luo et al., 2022; Tong et al., 2021). Companies such as Amazon, IBM, and Alibaba have already implemented AI-based performance monitoring systems to track employee productivity and deliver data-driven feedback (Heaven, 2020; Roose, 2020). This shift reflects a broader trend in automation, where AI is replacing or complementing human managerial functions. However, while AI-generated feedback offers consistency and data accuracy, concerns remain about employees' acceptance, given the perceived lack of emotional intelligence and personalized assessment (Dietvorst et al., 2015; Logg et al., 2019). Understanding how employees respond to AI-generated feedback versus human-generated feedback is thus crucial for organizations seeking to optimize performance management systems.

Despite the global push for AI-driven workplace technologies, the extent of AI adoption and employee acceptance varies across different institutional and cultural settings. In Western economies, AI-based decision-making is often met with skepticism due to concerns about fairness, transparency, and job security (Agrawal et al., 2019; Leicht-Deobald et al., 2019). In contrast, firms in technologically progressive regions, such as China and Singapore, have widely embraced AI-driven management control systems, with employees demonstrating greater adaptability to AI interventions (Jia et al., 2023). As a developing country, Bangladesh has experienced considerable advancements in digital technologies, particularly in the areas of artificial intelligence (AI) and automation. The government of Bangladesh has shown increasing interest in integrating AI into various sectors, including finance, healthcare, and education, as part of its broader vision to foster digital transformation (Bangladesh Digital Strategy, 2021). In parallel, many organizations in Bangladesh are adopting AI technologies within their management control systems to enhance productivity and decision-making processes (Hossain & Rahman 2023; Islam et al., 2024). However, the implementation of AI in organizational settings remains in its early stages (Islam et al., 2024), with challenges around employees' trust in AI and perceptions of its objectivity.

In this context, employee reactions to AI-generated feedback, especially within management control systems, have yet to be fully explored. Understanding how employees in Bangladesh perceive AI feedback, in comparison to human feedback, is crucial to optimizing AI integration and fostering positive workplace dynamics. This study contributes to filling this gap by examining the effects of AI versus human-generated performance feedback on employee behavior and performance within the institutional framework of Bangladesh's evolving technological landscape.

2.2 *Artificial intelligence versus human in decision making*

Management theory has recognized for more than a century that obtaining accurate information about the quality of employees' work is a crucial means of boosting productivity and increasing the value of a firm (Taylor, 1911). In this regard, employees' performance feedback involves the collection of data concerning their job-related actions, the assessment of their performance, and the provision of feedback aimed at enhancing their performance, constitute a pivotal facet of effective performance feedback management (Latham & Kinne, 1974; Tong et al., 2021). These activities represent the central "information role" of managers, requiring them to supervise the work environment, including employees, in order to create, handle, and share information within the organization. In the realm of data analytics, AI technologies are harnessed to formulate precise and exhaustive predictions (Agrawal et al., 2018; Jarrahi, 2018; Luo et al., 2021), indicating the capability of AI to fulfill these informational roles. However, firms continually implement AI technologies to perform labor-intensive mechanical tasks. For instance, Amazon uses AI algorithms to assess the warehouse employees' performance (Tong et al., 2021). Nonetheless, the use of advanced AI technologies to assess and furnish feedback to employees has gained prominence, as evident in Alibaba, Amazon, IBM, and MetLife.

The swift technological advancements have led to a significant rise in the automation of diverse facets within firm performance management systems (Jarrahi, 2018; Luo et al., 2019)., particularly emphasizing the process of providing employee performance feedback. A fundamental benefit of AI in decision making compared to humans is their prowess in processing hard data (Jarrahi, 2018; Luo et al., 2021). AI's inherent capability is exemplified by its aptitude for handling vast volumes of data, uncovering latent patterns within both structured and unstructured data (Jia et al., 2023; Luo et al., 2022; Tong et al., 2021). Scholars acknowledge that AI exhibits particular aptitude in tasks requiring extensive processing of textual, auditory, visual, and video data for decision-making, surpassing human capabilities in these regards (Agrawal et al., 2018; Brynjolfsson et al., 2019). With the advancing complexity of AI technologies, they can now execute numerous functions that were traditionally handled by humans, supplement human activities, and even surpass human performance (Chen et al., 2022; Fountaine et al., 2019). An AI-based performance feedback system constitutes a software solution that harnesses advanced deep learning neural network algorithms and natural language processing methodologies to assume a managerial function. For instance, within the domain of performance feedback, AI has the capacity to observe and record employees' work-related tasks, assess their performance, and even produce tailored feedback aimed at enhancing employee productivity(Luo et al., 2019; Tong et al., 2021).

Reynolds and Beatty (1999) posit that human contentment is essentially influenced by the interpersonal engagement between individuals and their alignment with organizations. The integration of AI in workplace assumes a scenario where interaction occurs between employees and AI supervisors without direct human intervention. Yet, feedback provided by AI could be subject to debate due to their potential lack of subjective judgment capability, limited experience of emotions and physical sensations (e.g., pleasure, hunger, pain), and moderate agency in thinking, planning, and acting (Gray et al., 2007; Yam et al., 2021).

A contentious discussion surrounds the potential replacement of humans by AI in furnishing workplace performance feedback. Some scholars contend that AI's data collection and analysis prowess surpasses human capabilities (Fountaine et al., 2019; Jarrahi, 2018). Conversely, certain scholars assert that individuals display "algorithmic aversion," favoring human judgment over algorithms (Dietvorst et al., 2015; Jarrahi et al., 2021). Despite AI's data analysis advantages, it lacks humans' soft interpersonal communication skills (Luo et al., 2019). The research of Cai et al. (2019) research demonstrates that human managers with transformational styles and strong interpersonal skills deliver more effective feedback than artificial intelligence. Additionally, other researchers have examined AI's dual positive and negative impacts on employee performance feedback, coexisting in various contexts (Tong et al., 2021).

However, the discourse concerning the complete substitution of humans by AI within firms' management control systems remains inconclusive within both scholarly and practical circles. This divergence of opinions has engendered contrasting perspectives among researchers and practitioners concerning the efficacy of AI as a replacement for human involvement in performance management systems. In light of this unresolved discourse, our research aims to provide substantial insights by conducting a comprehensive inquiry into the impact of AI-generated feedback on employee behavior and performance, contrasting it with the effects of human-generated feedback.

2.2 Hypotheses development

The advantage of AI lies in its technological superiority, characterized by its exceptional capacities in data collection, analysis, and precise prediction-making, which surpass the capacities of human counterparts (Jarrahi, 2018; Luo et al., 2019; Tong et al., 2021). AI systems, compared to humans, are designed to process massive amounts of data quickly and accurately, which is advantageous for providing employees with targeted and insightful feedback (Chen et al., 2022; Jia et al., 2023; Meyer et al., 2014). This capability naturally facilitates an extensive assessment of employee performance metrics, allowing AI to recognize subtleties and trends that might elude human observers. We posit that AI-generated feedback, as opposed to feedback from humans, operates within a structured framework of traceable and transparent rules, thereby enhancing its consistency and objectivity, which are crucial factors that influence employee learning. However, prior studies argue that human feedback, despite its contextual sensitivity, can inadvertently be influenced by subjective biases, emotional states, and individual variations in judgment (Mahmud et al., 2022; Tong et al., 2021; Yam et al., 2021). In contrast, AI feedback's consistency and objectivity offer a standardized assessment, fostering a sense of fairness and impartiality (Jia et al., 2023; Luo et al., 2022). We argue that the standardized approach of AI is particularly pertinent to learning, as it provides clear and unbiased insights into areas for improvement.

In addition, the integration of AI technology into the performance feedback procedure can take advantage of its capacity to personalize feedback delivery (Biswas et al., 2024; Tong et al., 2021). We contend that AI, through data analysis, can outperform humans by identifying each employee's strengths, limitations, and learning preferences, allowing for the customization of feedback to meet their specific requirements. The personalized feedback by AI fosters employee engagement to work, thereby enhance their learning. Thus, we propose the following hypothesis:

Hypothesis 1: Employees' learning under AI feedback will be higher than employees' learning under human feedback.

Based on the theory of perception, Gray et al. (2007) posits that individuals perceive the mental attributes of others based on two key dimensions: agency, encompassing cognitive capacities like thinking, planning, and acting, and experience, involving the capacity to undergo emotions and physical sensations such as pleasure, hunger, pain, and satisfaction. Empirical investigation into this theory has indicated that AI is generally perceived as possessing a moderate level of agency while having limited experiential capabilities, in contrast to humans who are attributed both high levels of agency and experience (Yam et al., 2021). Prior studies suggest that individuals' perception, acceptance, and response to a feedback are influenced by the decision's source (Ilgen et al., 1979; Luckett & Eggleton, 1991). When AI provide performance feedback, employees tend to perceive AI as devoid of emotions. AI systems lack the capability to comprehend or respond to employees' emotional states, which are pivotal in the realm of social interaction and the establishment of interpersonal relationships (Gray et al., 2007; Mahmud et al., 2022; Yam et al., 2021). These inherent limitations of AI can impede employees from engaging in meaningful communication and interaction with AI systems, thereby inhibiting the emotional resonance and activation among employees.

On the contrary, humans are capable of infusing a human touch into their feedback processes through the use of emotions and social skills (Belschak & Hartog, 2009; Madjar et al., 2017; Madrid et al., 2014). This approach allows for a deeper resonance with employees, ultimately eliciting emotional responses and triggering memorable experiences. We argue that AI-generated feedback tends to be more systematic and objective, potentially lacking the emotional nuances and empathetic components often inherent in human interaction. Furthermore, AI's reliance on data-driven analysis and algorithms might result in feedback that is more focused on performance metrics and less attuned to the emotional aspects of employee responses, potentially leading to decreased positive emotional arousal. This is in contrast to human feedback, which could involve more personalized and emotionally resonant communication, potentially resulting in higher positive emotional arousal among employees. Thus, we propose the following hypothesis:

Hypothesis 2**:** Employees' positive emotional arousal under AI feedback will be lower than employees' positive emotional arousal under human feedback.

When designed effectively, AI systems can process significant amounts of data with greater precision and speed than humans (Jarrahi, 2018; Jia et al., 2023; Tong et al., 2021). The ability of AI to analyze both structured and unstructured data, including textual and multimedia data, enables it to provide a comprehensive evaluation of employee performance, a capability that transcends that of humans (Bernhardt et al., 2023; Commerford et al., 2022; Luo et al., 2022). Moreover, AI can provide personalized and timely feedback at scale compared to humans. AI systems are able to perpetually monitor and assess employee performance, providing immediate insights and improvement suggestions (Luo et al., 2021; Tong et al., 2021). This real-time feedback cycle of AI enables employees to make timely adjustments, leading to improved performance outcomes. We argue that this data-driven approach assures that AI feedback is objective, unbiased, and based on an abundance of information, thus minimizing the possibility for human biases that could influence human evaluators' feedback.

In addition, prior study evidence that the ability of AI to recognize patterns and trends in employee performance data can result in more precise and individualized feedback than feedback provided by humans (Tong et al., 2021). AI is capable of identifying an individual's strengths and weaknesses, enabling employees to concentrate on areas requiring development while strengthening their existing competencies. This method of personalized feedback is frequently difficult for human evaluators to replicate consistently. We argue that the objective and data-driven nature of AI-generated feedback, based on concrete performance metrics and devoid of subjective judgments or personal biases, may foster a sense of trust in the performance feedback process among employees. Thus, we propose the following hypothesis:

Hypothesis 3**:** Performance feedback by AI will lead to higher employee performance than performance feedback by a human.

Yerkes and Dodson (1908) suggest that emotional arousal has a curvilinear effect on performance, where moderate arousal enhances focus and efficiency, but extreme arousal—either too low or too high—can hinder task performance. Emotional arousal influences how employees apply learned knowledge in real-world tasks. Research on emotions states that positive arousal broadens cognitive capacities and facilitates adaptive behaviors (Fredrickson, 2001), permitting employees to effectively integrate learned skills into performance. When employees experience moderate to high emotional arousal, they are more likely to involve deeply with tasks, increasing effort and motivation, which strengthens the learning-performance link (Watson & Tellegen, 1985). Additionally, Fredrickson (2001) claims that heightened positive arousal expands employees' cognitive flexibility and problem-solving abilities, making them more receptive to new information and enhancing their ability to apply learned knowledge to performance tasks. Conversely, excessively high arousal, particularly from stress or negative feedback, can impair cognitive flexibility and disrupt task execution (Easterbrook, 1959; Schmeichel & Tang, 2015).

Moreover, Tai and Chau (2009) implies that emotional states in a work environment influence employees' engagement with tasks. A positive emotional state, often induced by constructive feedback or successful learning experiences, can amplify employees' motivation to apply their knowledge to performance. On the other hand, excessive emotional arousal stemming from pressure or anxiety may lead to cognitive overload, reducing the effectiveness of learning on performance (Belschak & Hartog, 2009; Madrid et al., 2014). Accordingly, this study posits the following hypothesis:

***Hypothesis 4*:** Employees' emotional arousal plays a moderating role in the relationship between employees' performance and learning.

3. Methodology

3.1 Participants and manipulation

We recruited 48 students from a recognized Bangladeshi university, all of whom were enrolled in the full-time MBA program. The university students can be considered a suitable proxy for reasonably informed non-professional activities (Barton et al., 2014; Elliott et al., 2007; Libby et al., 2002). To bolster participant engagement in the experimental task, it was conveyed to them that they would receive a fixed compensation of $5 for their participation. The average age of participants was 26 years, and 42.52 percent of them were females. A 2 × 2 between-subject experimental design was employed to test our hypotheses. The two experimental factors were feedback source and feedback nature, each having two levels, resulting in a total of four distinct experimental groups. For our experiment, we randomly assigned 48 participants to each of these experimental groups, as outlined in Table 1.

Table 1 Experiment group

	Human supervisor Performance Feedback	AI Performance Feedback
Positive feedback	Group 1	Group 3
Negative feedback	Group 2	Group 4

3.2 Experimental equipment

We employed the Embrace 4 (E4) smart wristband, namely electrodermal activity (EDA), a device that records skin conductance, to determine participants' heart rate as an indicator of their learning levels and emotional arousal.[1] The EDA device, when worn on the ankle, enables the real-time acquisition of skin conductance data at a sampling frequency of 4 times per second (Caruelle et al., 2019; Li et al., 2022). The device is lightweight and ergonomically designed, causing minimal disruption to the experimental proceedings (Li et al., 2022). Its operation is straightforward, and real-time data monitoring is facilitated through the E4 real time application. The recorded data is securely stored in the cloud and can be subsequently downloaded from the official E4 connect website.

3.3 Experimental task and procedure

We employed a symbol translation task, adapted from earlier research conducted by Chow (1983) and Church et al. (2008). This task included various lines of symbols along with a

[1] A small sample size is commonly observed in business research utilizing electrodermal activity (EDA) measures, with sample sizes ranging from 2 to 240, and the majority consisting of fewer than 50 participants (Caruelle et al., 2019; Li et al., 2022).

corresponding translation key. Participants were tasked with deciphering these symbols and converting them into their respective alphabetical letters using the supplied key. For reference, both the translation key and examples of symbol lines can be found in the Appendix.

Each participant was scheduled to arrive at the designated experimental office at a predetermined time slot, and they were subsequently allocated to one of the four groups outlined in Table 1. At the outset of the experiment, the researcher provided each participant with the necessary instructions, which were also read aloud for clarity. Following the instructional phase, participants were assisted in donning the Electrodermal Activity (EDA) device. After EDA placement, participants were instructed to sit quietly for a two-minute period, during which their eyes were to remain closed, and they were encouraged to achieve a state of mental relaxation. During this interval, baseline measurements pertaining to heart rate, as a measure of learning, and emotional arousal were recorded. The experimental task itself encompassed two distinct rounds. In each round, participants were presented with worksheets comprising eight rows, each containing ten symbols. They were allotted five minutes for the translation of as many symbols as possible. Instructions directed participants to proceed sequentially, addressing all symbols within a given row before advancing to the subsequent line.

Upon the conclusion of the first round, participants received performance feedback from their assigned supervisors. we created two distinct feedback conditions: AI-generated voice feedback, synthesized using ElevenLabs, and human-generated voice feedback, recorded by a professional speaker to ensure consistency in tone and delivery. Half of the participants, encompassing both the human feedback and AI feedback groups, were received positive performance feedback, while the remaining participants within these two groups received negative performance feedback. Subsequent to the receipt of their performance feedback, participants commenced the second round of the experimental task. Upon the completion of the task, the EDA devices were removed from the participants. A post-experimental questionnaire was then administered, encompassing a manipulation check, demographic inquiries, and a series of questions designed to elicit participants' perspectives on the experiment.

3.4 Measurement of variables

3.4.1 Independent variable

Feedback source = an indicator variable that takes the value of 1 (0) if participants received AI feedback (human feedback).

Feedback nature = an indicator variable that takes the value of 1 (0) if participants received positive feedback (negative feedback).

3.4.2 Dependent variable

Employee learning: Human heart rate is a physiological reactivity, which manifests as changes in learning during a task (Darnell & Krieg, 2019; McCraty, 2015). In this study, participants' heart rate serves as a measure of their learning. The heart rate recorded from each participant during the resting phase was established as the baseline value, whereas the heart rate measured during the experimental task served as the comparative value. Therefore, employee learning is quantified as the changes between percentage of these two values.

Emotion arousal: Electrodermal activity (EDA) is a psychophysiological indicator of emotional arousal (Caruelle et al., 2019; Li et al., 2022). In this study, participants' EDA serves as a measure of their emotional arousal. The EDA level recorded from each participant during the resting phase was established as the baseline value, whereas the EDA measured during the experimental task served as the comparative value. Therefore, emotional arousal of participants was measured as the percentage changes between these two values.

Employee performance: Performance was measure by the number of symbols correctly decoded by participants during the experiment following the methodological approach established in previous studies (Chow, 1983; Church et al., 2008).

4. Results and discussion

4.1 Manipulation check

To assess the effective manipulation of feedback source, participants were queried regarding the voice of their supervisor. Specifically, the distinction between various performance feedback sources lies solely in the difference in voice. Therefore, the participants' ability to accurately discern whether their feedback source is a human or AI is vital to the experimental results. To ascertain distinctions of the feedback sources, participants were inquired, at the end of the experiment, to rate "To what extent the voice resembles a human voice" on a seven-point scale, where 1 indicates "not at all," and 7 signifies "very similar." A one-way between group ANOVA was conducted to assess variance in responses between two distinct feedback sources groups. The outcomes reveal a noteworthy dissimilarity in participants' responses to this inquiry when comparing the AI performance feedback group to the human supervisors' feedback group ($F_{1,46}$ = 19.54, p = 0.000). This statistical significance suggests that participants exhibit the capacity to effectively discriminate between the sources of performance feedback, distinguishing between AI and human supervisors as the originators of the feedback.

4.2 Hypotheses testing

Figure 1 illustrates the distribution of learning, emotional arousal, and performance scores in our study. In this context, human feedback providers are categorized into two groups: humans providing positive feedback (HP) and humans providing negative feedback (HN). Similarly, AI feedback providers are classified as AI with positive feedback (AP) and AI with negative feedback (AN). The results indicate that HP elicits the highest levels of emotional arousal compared to HN, AP, and AN, while AP and AN combined exhibit lower emotional arousal than HP and HN. Additionally, learning scores under AN significantly exceed those under HP, AP, and HN, with AP and AN collectively leading to higher learning levels than HP and HN. Notably, while HP yields the highest employee performance among individual conditions, the combined performance of AP and AN surpasses that of both HP and HN. The results indicate that while human-provided positive feedback (HP) elicits the highest emotional arousal, AI feedback (AP and AN) collectively leads to lower emotional responses, aligning with H2. However, AI-driven negative feedback (AN) results in the highest learning outcomes, with AI feedback overall enhancing learning more than human feedback, supporting H1. In terms of performance, although HP individually leads to the highest performance, AI feedback (AP and AN) combined surpasses both human feedback conditions (HP and HN), suggesting that AI-driven performance evaluations may be more effective in enhancing employee performance, which aligns with H3.

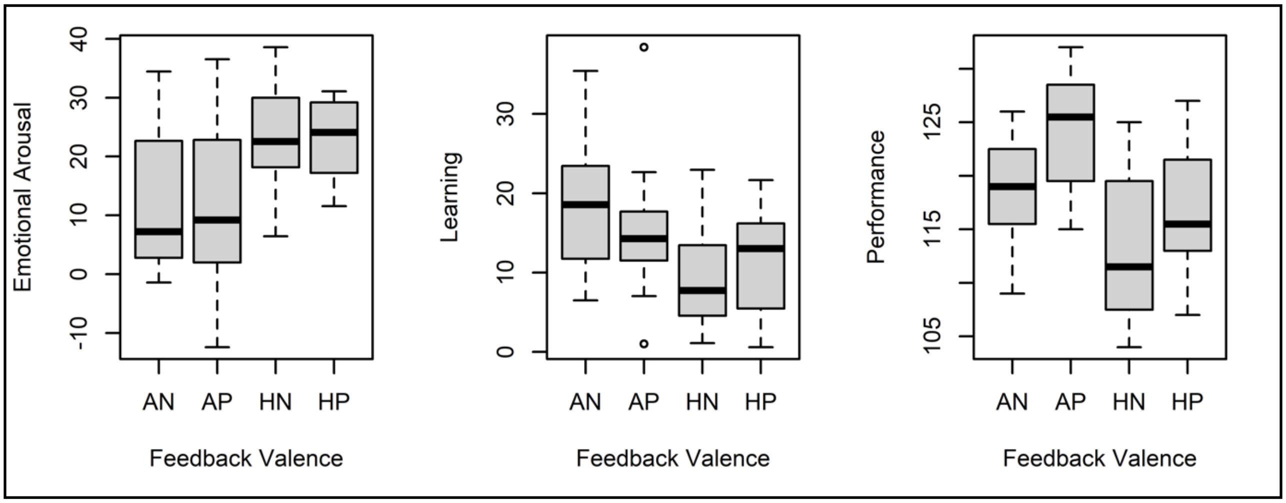

Figure 1

Given that the distribution of data is unknown and the sample size is not large, we apply a nonparametric test (Mann-Whitney U test) to compare the median of outcomes obtained from two different types of feedbacks made by AI and Human. Mann-Whitney U test is equivalent to the Wilcoxon rank sum test and is used in place of an unpaired t-test. This tests the hypothesis whether observations in one sample is larger than the other sample. For example, given a set of observations in two experiments $\{x_1, x_2, \dots x_n\}$ and $\{y_1, y_2, \dots y_n\}$, each $x_i$being greater or smaller than each y_i has an equal chance if both samples have the same median. Thus, in practice, Mann-Whitney U test defines null and alternative hypotheses of the form

$$H_0: P(x_i > y_i) = \frac{1}{2};\ \ H_1: P(x_i > y_i) > \frac{1}{2}$$

to test that $x_i$being greater than y_i for $i = 1, \dots, n$. Based on this hypothesis defining procedure, we provide mathematical presentation of our hypotheses and provide test results in Table 2.

Table 2
Mann-Whitney U test

Measure	**Hypothesis**	**Statistical Form**	**W-statistic**	**p-value**	**Supports the H_{1a}**
Learning	H_{1a}	$H_{1a}: P(LAI > LHU) > \frac{1}{2}$	414	0.004***	Yes

Emotional Arousal	H_{2a}	$H_{2a}: P(EHU > EAI) > \frac{1}{2}$	438	0.001***	Yes
Performance	H_{3a}	$H_{3a}: P(PAI > PHU) > \frac{1}{2}$	437	0.001***	Yes

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. Any p-value less than 0.10 refers to the rejection of the null hypothesis defined against the hypotheses H_{ia} and H_{ib} for $i = 1,2,3$. Here, LAI = Employees' learning under AI feedback, LHU = Employees' learning under human feedback; EHU = Employees' emotional arousal under human feedback, EAI = employees' emotional arousal under human feedback; PAI= Employees' performance under AI feedback, PHU= Employees' performance under human feedback.

The statistical results strongly support the first three hypotheses. For Hypothesis 1**,** the analysis shows that employees' learning under AI feedback (LAI) is significantly higher than under human feedback (LHU) (W = 414, p = 0.004), confirming that AI-driven feedback enhances learning outcomes. The findings of this study align with prior research on AI-driven management control systems and performance feedback. The higher learning outcomes under AI feedback are consistent with previous studies suggesting that AI leverages vast datasets and objective algorithms to deliver precise, data-driven feedback, facilitating better learning (Fountaine et al., 2019; Tong et al., 2021). AI's ability to provide consistent and detailed performance assessments may reduce ambiguity in feedback interpretation, leading to greater knowledge acquisition.

For Hypothesis 2**,** the results indicate that employees' positive emotional arousal is significantly lower under AI feedback (EAI) compared to human feedback (EHU) (W = 438, p = 0.001), supporting the idea that AI-generated feedback lacks the interpersonal qualities that contribute to emotional engagement. The lower emotional arousal under AI feedback corroborates earlier studies on algorithmic aversion and the perception of AI as impersonal (Dietvorst et al., 2015; Logg et al., 2019). AI lacks the human capacity for empathy, social bonding, and motivational cues, which may reduce employees' emotional engagement with AI-generated feedback (Gray et al., 2007; Yam et al., 2021).

For Hypothesis 3, the findings reveal that performance under AI feedback (PAI) is significantly higher than performance under human feedback (PHU) (W = 437, p = 0.001), suggesting that AI-driven performance evaluations enhance employee performance more effectively. The higher employee performance under AI feedback supports research indicating that AI-driven feedback systems enhance performance by providing objective, traceable, and unbiased evaluations (Biswas et al., 2024; Brynjolfsson et al., 2019; Jarrahi, 2018). This result suggests that AI-based systems may mitigate issues related to human bias and inconsistency in performance evaluation, leading to improved employee outcomes.

We would like to explore the effect of emotional arousal (EAR) and learning (LRN) on performances (PRF) of employees. A multiple regression model that essentially reflects the joint effects of LRN and EAR can be estimated as

$$\widehat{PRF} = 6.05 * LRN + 4.43 * EAR - 0.22 * LRN * EAR$$

where each of these above coefficients are significant at 1% level and the coefficient of multiple determination $R^2 = 0.93$. Thus, emotional arousal seems to moderate the effect of learning on performance achieving. Given the mean level of learning (LRN) of employees, we plot the effects of emotional arousal on performance in Figure 2 supporting hypothesis 4.

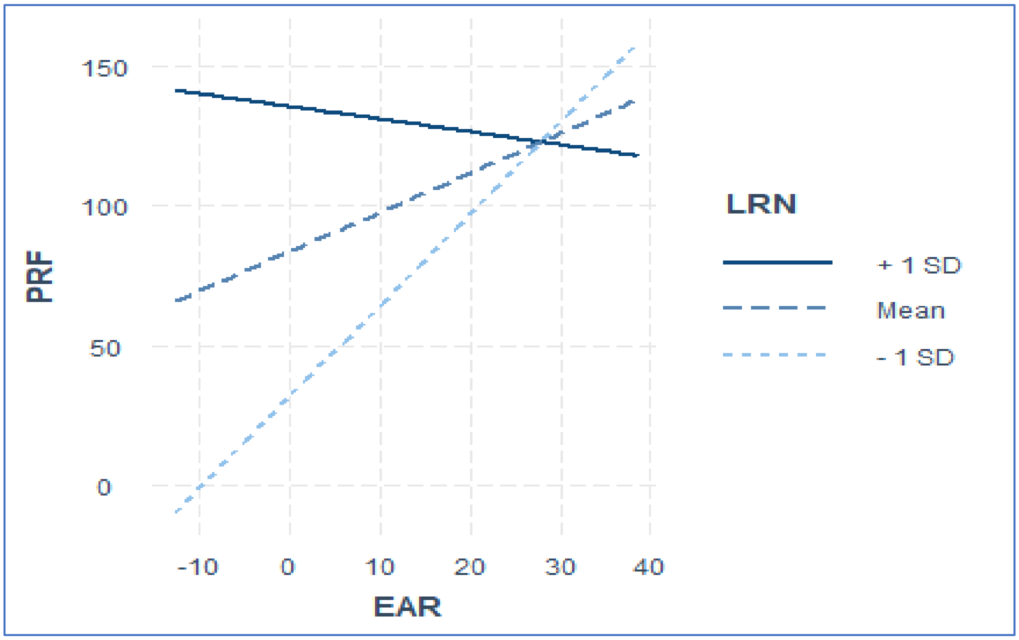

Figure 2: Effect of emotional arousal (EAR) on performance (PRF) for learning (LRN)

Given the mean learning level of employees, performance is predicted to increase with the increase of emotional arousal, however, the confidence interval gets wider for very high and low emotional arousal levels, align with the findings of Yerkes and Dodson (1908). Such wider confidence interval is attributed to very low emotional arousal representing less responsiveness to the consequence of feedback or to very high emotional arousal representing too much anxious to the consequence of feedback. The positive moderating effect of emotional arousal is consistent with prior research demonstrating that moderate emotional activation enhances cognitive flexibility, information processing, and motivation (Fredrickson, 2001; Schmeichel & Tang, 2015)**.**

5. Conclusion

This study contributes to the growing literature on AI in management control systems by providing empirical evidence on the impact of AI-generated performance feedback on employee learning, emotional arousal, and performance. The findings support all four hypotheses, demonstrating that AI feedback enhances employee learning more effectively than human feedback, elicits lower positive emotional arousal, and leads to higher employee performance. These results highlight the potential of AI as a feedback provider, particularly in improving learning and performance outcomes. This study also advances theoretical understanding by integrating the Theory of Perception to explain how employees interpret and respond to AI-generated feedback compared to human feedback. By demonstrating that AI feedback enhances learning and performance while eliciting lower emotional arousal, this research extends existing theories on feedback effectiveness and algorithmic aversion in management control systems. Moreover, this study offers practical implications for organizations considering AI integration into their performance evaluation processes, suggesting that AI-driven feedback systems can enhance employee development while acknowledging potential emotional drawbacks.

Despite these contributions, this study has some limitations. First, the experimental design, while controlled, may not fully capture the complexities of real-world workplace dynamics, where social and organizational factors influence feedback reception. Second, the short-term nature of the experiment does not account for potential long-term effects of AI feedback on employee motivation, trust, and job satisfaction. Third, the study focuses on AI and human feedback in isolation, but hybrid models that combine AI-generated insights with human judgment may yield different outcomes. Future research could explore the long-term psychological and behavioral effects of AI feedback in organizational settings, investigate how employees adapt to AI-based evaluations over time, and examine whether industry-specific factors influence the effectiveness of AI feedback. Additionally, further studies could assess the impact of AI-human collaborative feedback models to determine optimal strategies for integrating AI into management control systems.

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