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Presenteeism in the Age of AI: How generative intelligence tools behave on presenteeism decision-making scenarios

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Masters in Human Resource Management and Organizational Consultancy

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Doctorate Professor Aristides Isidoro Ferreira, Associate Professor,
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Department of Human Resources and Organizational Behavior

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“I truly believe that the only way we can create global peace is through not only educating our minds, but our hearts and our souls.”

Malala Yousafzai

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To my supervisor, whose guidance was beyond words. I will forever be grateful for the patience, for challenging me to reach higher, and for providing me with not only knowledge, but also human kindness, which altogether left an incredible mark on this work. This achievement would not be possible without your investment of time, knowledge, and belief.

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This achievement is as much yours as it is mine.

RESUMO

O presentismo, fenómeno em que os colaboradores trabalham apesar de doentes, tem despertado crescente interesse académico, dado o seu impacto na produtividade e bem-estar dos colaboradores. Paralelamente, a integração de ferramentas de inteligência artificial (IA) na gestão de recursos humanos (RH) levanta questões sobre a capacidade destes sistemas para lidar com dilemas complexos e subjetivos, como os associados ao presentismo. Este estudo propõe-se a comparar a tomada de decisão entre ferramentas de IA e gestores de recursos humanos em cenários de presentismo, enquadrando-se na Dual-Process Theory e em modelos de liderança. A investigação centra-se em três questões principais: (1) se a variação nas avaliações difere entre humanos e sistemas de IA, (2) se ambos distinguem adequadamente os diferentes tipos de cenário e (3) se existem padrões sistemáticos nas decisões de cada grupo. Para tal, foi desenvolvido um teste de julgamento situacional, aplicado a uma amostra composta por 119 gestores de RH e cinco ferramentas de IA, cada uma exposta a oito cenários distintos. Os resultados revelam que as ferramentas de IA apresentam maior consistência e racionalidade, embora com estilos de liderança variados. Em contraste, os gestores de RH demonstram maior variabilidade, combinando lógica com intuição baseada na experiência. Estes resultados sugerem que, apesar da eficiência da inteligência artificial, a sua capacidade de raciocínio ético permanece limitada. Assim, o estudo reforça a importância de uma supervisão crítica na delegação de decisões sensíveis a agentes não humanos, contribuindo para o debate sobre o futuro dos processos de tomada de decisão.

Palavras-chave: Inteligência Artificial; Presentismo; Tomada de Decisão.

JEL: M12; M15

ABSTRACT

Presenteeism, the phenomenon where employees attend work despite illness, has continuously gained scholarly attention, with research highlighting its adverse effects on productivity, and employee well-being. As artificial intelligence (AI) tools become increasingly integrated into human resource (HR) operations, questions arise about how these systems interpret and respond to complex subjects, such as presenteeism scenarios. The present investigation explores how AI tools compare to human HR managers in evaluating and resolving presenteeism dilemmas. Grounded in Dual-Process Theory and leadership frameworks, three core research questions are addressed: (1) whether the variation in evaluations of presenteeism scenarios differs between HR managers and generative intelligence tools, (2) whether both groups differentiate between distinct presenteeism scenarios and (3) whether there are systematic differences in the evaluations provided by human and algorithmic decision-makers. A situational judgements test (SJT) was developed to assess decision-making across both groups, with a sample comprising 119 HR managers and five AI tools, each presented with eight presenteeism scenarios. Findings reveal that AI tools varied less between them and tended for more rational cognition but differing in leadership styles. Contrastingly, human participants demonstrated higher variance in decisions and a link between rational and experiential cognition behaviour. The findings suggest that while AI tools may offer consistency and speed in decision-making, they may lack the nuanced ethical reasoning required in complex, human-centred contexts. The study contributes to ongoing discussions on the future of HR decision-making, emphasizing the need for critical oversight when delegating sensitive workplace judgments to non-human agents.

Keywords: Artificial Intelligence; Decision Making; Presenteeism

JEL: M12; M15

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1. INTRODUCTION

Over the last years, organizations have increasingly used artificial intelligence (AI) tools to augment decision-making processes across various circumstances, including human resource management (Budhwar et al., 2023). As digital transformation is shaping traditional processes and operations, human resource (HR) departments become heavily pressured to evolve from merely administrative units to important strategic partners, becoming responsible not only for recruitment and performance monitorizations and management, but equally undertaking employee well-being and other evolving concerns, to remain competitive (Okatta et al., 2024). Within this metamorphosis, AI has emerged as a powerful and valuable tool which enables data-driven insights and predictive analytics, previously time and resource consuming (Jia et al., 2023), which improves decision-making. However, while AI application in human resource management (and management overall) has primarily been focused on efficiency and performance metrics (Guenole, Ferrar & Feinzig 2017), there is still a meaningful gap in leveraging AI tools and its use to address more human-centric concerns, especially employee health and well-being.

One concern that has gained scholarly attention is presenteeism. Presenteeism is the phenomenon where employees attend work despite being ill (Hemp, 2004), leading to reduced productivity (Karanika-Murray & Biron, 2019) and severe health consequences on the long run (Martinez & Ferreira, 2011). Likewise, presenteeism is translated into a silent but impactful threat to both employee engagement and organizational effectiveness. Unlike absenteeism, which is easily tracked, presenteeism is “veiled”, making it a more significant challenge for organizations and, in most cases, humans resources teams and professionals. Moreover, traditional methods of identifying and undertaking presenteeism, such as surveys, often fail to seize the nuanced behaviours and early warning signs of diminished well-being. Accordingly, there is an urgent need for enhanced proactive, accurate and data-based tools to help human resource professionals support health-related decision-making tasks.

The present study aims to explore the comparative effectiveness of decision-making between artificial intelligence tools, such as generative intelligence, and human resource managers, under presenteeism contexts. It aims to understand how AI-driven decision-making differs from the one made by humans, and how it can help human resource managers, when the focus is efficiency, accuracy, and overall direct and indirect impact on the broader organizational outcomes. With the easy availability of reliable data, and affordable computer

technology, artificial intelligence is becoming more and more relevant (Gupta & Kumar, 2024). The greater reliance on artificial intelligence in different business areas, such as human resource management, affects extents such as recruitment, performance evaluation, and talent management. These applications bring critical questions regarding the role and effectiveness of AI in complex, health-related decisions, when compared to human decision-making processes. Although perceived as beneficial, it is crucial to understand whether AI can effectively improve decision quality without compromising human judgement, and the personal touch often required in human resource functions (Cappelli, Tambe & Yakubovich, 2019). When decisions often involve assessing risks to employee health and safety, AI's ability to process large amounts of data quickly offers significant advantages. However, whether artificial intelligence appropriately integrates the human-centred judgment required for sensitive health-related discussions remains an open issue. Having this in mind, the present research aims to answer three questions:

1. Is the variation between HR managers' and algorithms' evaluations of presenteeism scenarios equal?
2. Do both algorithms and HR managers differentiate between different presenteeism scenarios?
3. Are there differences between evaluations given by algorithms and HR managers?

To address these questions, the present research is divided in five sections. *Theoretical Framework* provides a comprehensive review on existing literature on presenteeism, artificial intelligence, and the evolving role of digital transformation within human resource management. *Methodology* outlines the research methodology, including the scenario design, sampling strategy and data analysis procedures. The *Results* chapter presents the study's findings through quantitative comparisons and qualitative evolution of response justifications. After, *Discussion* presents the interpretation of results, implications and links the findings to the existing theories and practices. Finally, the last chapter highlights limitations and proposes directions for future research, reflecting on the evolving relationship between technology and human-centred decision-making in organizations.

The research proposed responds to an increasingly relevant question: as AI platforms become part of human resource processes, are they equipped to handle sensitive judgments with the same level of ethical discernment and contextual nuance as human experts? Through statistical analysis thematic explanation and theoretical framing, this thesis sheds light on how decision logic, communication style, and scenario conditions interact in guiding workplace judgments, and what this might mean for the future of organizational decision-making.

2. THEORETICAL FRAMEWORK

2.1. Presenteeism

Presenteeism has become an increasingly pressing issue in recent years, drawing attention from both researchers and organizational leaders. Unlike absenteeism, which is immediately visible, quantifiable and explained by physical absence of the workplace (Cancelliere et al., 2011; Kocakulah et al., 2016; Tarro et al., 2020), presenteeism is far more insidious. Presenteeism is referred to as the phenomenon when employees remain at work but, due to illness or other medical conditions, not fully achieve their potential and productivity (Ferreira et al., 2017; Hemp, 2004; Karanika-Murray & Biron, 2019; Karanika-Murray & Cooper, 2018). At first glance, presenteeism may not seem as costly as absenteeism as, after all, employees are still physically present and still try to fulfil their work responsibilities. However, this perception becomes misleading (Cancelliere et al., 2011; Karanika-Murray & Biron, 2019). By manifesting itself in subtle ways, such in the form of reduced efficiency, lower cognitive engagement and potentially exacerbated health conditions, it may easily go unnoticed (Hansen & Andersen, 2008) and inflict long-term consequences on both employees and the organizations (Bierla et al., 2013). In other words, without being properly undertaken, presenteeism not only exacerbates individual health conditions (Ruhle, et al., 2019), but also leads to compounding workplace inefficiencies that ripple through teams, departments, and entire businesses (Karanika-Murray & Biron, 2019; Miraglia & Kinman, 2017).

It is important to distinguish presenteeism from intentional disengagement. Hemp (2004) states that presenteeism is not about “malinger – pretending to be ill to avoid work duties – or goofing off on the job – surfing on the internet, for example”. Employees, despite their health condition, avoid skipping work and remain trying to carry on with their tasks, often motivated by fear (Ferreira et al., 2017; Kinman, 2019; Kinman & Grant, 2020): fear of losing their jobs, or even of jeopardizing their careers. Whether driven by personal insecurities or workplace cultures that glorify long working hours, many employees feel they have no choice but to push through, even when their bodies and minds signal that they need rest (Kinman & Grant, 2020).

Accordingly, to comprehensively examine presenteeism, it becomes crucial to consider its underlying causes. Under the researcher’s scope, two distinct approaches to presenteeism are presented and, despite their different focal points, each makes significant contributions to a comprehensive understanding of presenteeism (Johns, 2010). On one hand, there is a predominantly North American and economically oriented approach, which conceptualizes

presenteeism as a source of productivity loss (Ferreira et al., 2017; Robertson & Cooper, 2011), with health being regarded as one of the most significant factors affecting employee productivity. Within this framework, researchers primarily focus on the consequences of attending work while ill, rather than on understanding the underlying causes (Kinman & Grant, 2020). On the other hand, another perspective examines the frequency of presenteeism behavior, seeking to identify variables that may enhance or provoke such occurrences (Cooper & Lu, 2018; Lohaus & Habermannb, 2019). This framework is more commonly associated with European countries, and according to this body of research, the decision to attend work while unwell is ultimately contingent upon an individual assessment of one's health status, as explained by Aronsson and Gustafsson (2005). However, the employee's decision may also be influenced by both internal and external factors (Johns, 2010). Several studies indicate that external or contextual factors, such as workplace insecurity, time pressure, insufficient work resources, limited career advancement opportunities and organizational culture are associated with presenteeism (Miraglia & Johns, 2016; Murir et al., 2008). For example, organizational norms that discourage taking sick leaves or working from home contribute to a work environment in which employees feel obligated to prioritize professional responsibilities rather than personal health and well-being (Kinman, 2019). Furthermore, high-pressure and overreliance on performance score environments (CIPD, 2016), which demand continuous outputs, often lead employees to disregard their health in order to maintain their productivity. While for the internal factors, the literature identifies financial difficulties, job insecurity, stress, personality traits, moral values, excessive commitment, individual predispositions, and a lack of personal boundaries as the most common individual causes of presenteeism (Aronsson et al., 2000; Hemp, 2004; Johns, 2010; Miraglia & Johns, 2016).

Employees work regardless their illness, which has an impact on both the quantity of work, as people might work more slowly than usual, and the quality, as they might make more, or more serious mistakes (Kinman & Grant, 2020). However, as mentioned above, presenteeism is not only detrimental to employees but also brings significant costs to organizations (Cancelliere et al., 2011). While individual performance reflects an immediate effect, long-term consequences extend, resulting in increased health-related expenses and heightened workplace inefficiencies, creating a never-ending cycle in which, although most of the medical conditions that provoke presenteeism are relatively benign (Hemp, 2004), afterwards, employees become more susceptible to chronic health issues (Kinman, 2019; Kinman & Grant, 2020; Martinez & Ferreira, 2011). This implicates prolonged medical interventions and lead to decreased workforce sustainability (Skagen & Collins, 2016). For instance, on a study on Portuguese

public hospitals, Martinez and Ferreira (2011) proved that the main causes of nurses' presenteeism were related to back pain, breath infections, migraines and also stress, and that employees with a "longstanding health condition had a tendency to adapt to their work in such a way that their problem did not obstruct their performance at their job". Moreover, the subsequent effect of presenteeism on team dynamics and interpersonal relations should not be overlooked, as diminished cognitive functioning and decreased morale among affected individuals can negatively impact and influence overall collaboration and team effectiveness (Kinman, 2019).

Given its complexity and having in mind that presenteeism has emerged as a growing organizational issue with multifaceted consequences and that employees continue to engage in this behavior (Karanika-Murray & Biron, 2019), organizations must develop and implement effective strategies that capacitate them to mitigate this phenomenon occurrence, justifying the increasingly importance of analyzing and understanding how decisions are made regarding this subject (Kinman & Grant, 2020). In addition, leadership plays a crucial role in shaping employees' perceptions of workplace expectations (Kranabetter & Niessen, 2017), therefore it becomes important that "human resource managers decrease negative effects of presenteeism by attending to job security, supervising and worker support" (Martinez & Ferreira, 2011). Furthermore, it is important to understand how managers decide on presenteeism situations, analyze the extent to which they believe flexibility is a greater tool to decrease presenteeism and rates, and overall benefit organizational outcomes, while taking better care of employee's needs.

2.2. Health Condition

Health is more than just the absence of illness, it is an ever-changing state that influences a person's physical, mental, and social well-being. The World Health Organization (2020) defines health condition as "any state that affects an individual's physical, mental or social well-being", ranging from minor ailments to severe diseases. Research has long emphasized that health is one of the strongest predictors of presenteeism, even more so than of absenteeism (Aronsson & Gustafsson, 2005; Johns, 2010). Often, employees find themselves navigating a difficult decision: whether to push through an illness and continue working or to step back and prioritize recovery.

Presenteeism, as seen above as the act of working while unwell (Karanika-Murray & Cooper, 2018), is not just about showing up at the office, but a reflection of deeper struggles between personal well-being, workplace expectations and professional obligations. By

definition, it requires that for presenteeism to occur, the employee must be experiencing some form of illness (Miraglia & Johns, 2016), meaning their ability to function at full capacity is inevitably compromised. Considering this, health status is an inseparable factor in presenteeism, as it is included in the very definition of the construct: “attending to work while being ill, consequently not performing in optimal condition due to health problems or other medical conditions” (Aronsson et al., 2010; Hemp, 2004; Johns, 2010).

Looking into detail, several medical conditions have been frequently associated with high presenteeism rates, including headaches or migraines, allergies, nasal issues, asthma, and dermatitis (Martinez & Ferreira, 2011), as well as musculoskeletal pain (Pohling, et al., 2016), diabetes (Breton et al., 2013), cardiovascular issues, respiratory problems, influenza, or the common cold (Gordoio et al., 2016). Also, from a psychological perspective, depression and anxiety are particularly notable in relation to presenteeism (Koopman et al., 2002).

Johns (2010) model of presenteeism examines the psychology behind these decisions, integrating two existing research lines, exploring the dynamic interplay between its causes, decision-making process, and consequences. His framework highlights that the occurrence of illness or discomfort becomes the trigger for the decision-making process, where self-assessment of the severity and nature of the illness, whether chronic (e.g. lower back-pain) or temporary (e.g. allergies), plays a crucial role. According to the Centers for Disease Control and Prevention (2024), chronic health conditions reflect a “illness that lasts one year or more and requires ongoing medical attention or limit daily activities”, while temporary health conditions are “short-term illnesses or injuries that typically resolve within a few weeks or months without requiring prolonged medical care”. The literature has suggested that less severe or benign conditions, those that do not necessarily prevent individuals from attending work, tend to lead to higher presenteeism rates (Hemp, 2004). The choice to work through an illness depends on how an individual perceives their own condition, rather than just the severity of their symptoms. Employees consider in what state they are in, whether their symptoms might improve or worsen throughout the workday, and how much pressure they feel to be present, despite the potential toll on their health. Overall, their perception of their health status and ability to reverse or mitigate symptoms (Lohaus & Habbermannb, 2019) demonstrates that an individual’s perception of their overall health condition is a crucial factor in the decision about attending work despite their condition (Johns, 2010).

For managers, making these assessments is particularly challenging. Deciding whether an employee should work despite illness is a delicate balance between supporting individual well-being and maintaining productivity within the organization. The difficulty in evaluating

someone else's health status, combined with the pressures of workplace culture, expectations, and leadership attitudes, makes presenteeism a complex issue that extends far beyond individual decisions. Finally, the way workplaces approach health, flexibility, and performance dictates whether presenteeism remains an unavoidable reality or becomes an opportunity for systemic change that better protects both employees and organizational outcomes.

2.3. Work arrangements

Work arrangements define the structure and conditions under which employees perform their job responsibilities, shaping everything from location to flexibility and employment type (McNall et al., 2010; Shifrin & Michel, 2022). According to Singh and Ramdeo (2023), these arrangements are influenced by various motivations, such as cost reduction and employee satisfaction, demonstrating how different work structures impact productivity and presenteeism.

As explained above, the way organizations design their work environments plays a major role in shaping presenteeism behaviors. Employees may prioritize company performance over their own well-being, especially in workplaces where strict attendance policies, high job demands, and limited flexibility create pressure to work despite illness (Johns, 2010). Work regimes, including the formal and informal values and rules governing workplace attendance, performance expectations and flexibility, play a pivotal role in shaping presenteeism behaviors among employees. Organizations with rigid attendance policies, high job demands, and limited flexibility often foster environments where employees feel compelled to work despite illness, contributing to presenteeism (Aronsson & Dallner, 2005). On the contrary, work structures that incorporate adaptable scheduling, remote work options and employee well-being initiatives help to mitigate presenteeism and promote healthier decision-making (Lohaus & Habermannb, 2019).

The relationship between work regimes and presenteeism is explored in various organizational behavior theories. Jobs with high demands and limited resources contribute to stress and work pressure, increasing presenteeism rates, which is proposed by Demerouti et al. (2001) through the Job Demands-Resources (JD-R) Model. Employees in demanding roles may choose to work while being sick to avoid falling behind or losing employment benefits and opportunities. Demerouti et al. (2001) explain that every job has its own resources (e.g. autonomy or co-worker support) and demands (e.g. workload or emotional demands). For the wellbeing of employees, these demands and resources must be balanced. Likewise, on one hand, employees may suffer from burnout and reduced job satisfaction when job expectations

are high, and resources are scarce. This means that if the demands are too much for the person to handle, their performance suffers from physical and mental health issues. On the other hand, workers are more likely to be motivated, engaged, and productive when there are enough resources to meet needs. Under this specific context, work regimes, and the flexibility to work from home when needed becomes a successful job resource to augment employee's health and well-being.

Psychological safety also plays a crucial role in presenteeism. The degree to which employees feel secure in making health-conscious decisions without fear of repercussions influences presenteeism occurrence as Edmondson (1999) explores through the Psychological Safety Theory. In fact, employees under environments that prioritize well-being and allow work absences without penalties are less likely to work while sick. Presenteeism is deeply embedded in workplace norms and consequently, different work regimes impact presenteeism occurrence differently. Rigid work environments, commonly practiced under industries such as healthcare, retail and manufacturing, often impose strict attendance policies, making employees feel obligated to work even when unwell (Bierla et al., 2013; Grailey et al., 2021). In fact, in a culture where presenteeism is commonly understood as dedication, employees believe that working while sick demonstrates commitment to their role (Hemp, 2004). On the other side, organizations that incorporate remote work, adjustable schedules and paid sick leaves tend to reduce presenteeism. This occurs because employees feel less pressured to perform while sick and can recover without feeling guilty or perceived as low performers (Kinman, 2019; Steward et al., 2003). In other words, offering hybrid work models and remote work options allows employees to balance health needs with job responsibilities, without them fearing negative repercussions (Johns & Xie, 1998; Shifrin & Michel, 2022).

The discussion around work arrangements and organizational culture is highly relevant as these elements shape how presenteeism occurs, and how HR managers perceive and approach health-related work decisions.

2.4. AI Acceptance and Use Climate

Gerlich (2023) defines artificial intelligence Acceptance as “the degree to which individuals and organizations perceive artificial intelligence as beneficial, trustworthy, and aligned with their operational needs”. AI acceptance is not merely about adopting new technology but represents a fundamental shift in how organizations structure their work environments, shape managerial attitudes and impact positively employee well-being. Organizations that embrace technological advancements, such as by offering flexible work models (Bailey & Kurland,

2002; Shifrin & Michel, 2022), automated decision-making tools and AI-driven health support systems (Schultz & Edington, 2007) foster more adaptive work environments, reducing presenteeism. Furthermore, technological embracement fosters flexible managerial attitudes, making decision-making more adaptable, personalized and data informed (Miraglia & Johns, 2016; Neumann et al., 2022).

Having this in mind, AI-driven collaboration tools, such as virtual workspaces, automated task distribution and cloud-based platforms, allow employees to perform their duties remotely, mitigating the need to work while sick in a traditional office, and overall contributing to reduce presenteeism rates (Bailey & Kurland, 2002). Accordingly, platforms like Microsoft Teams and Zoom enable employees to remain engaged with their teams even when working from home, while AI-driven scheduling systems accommodate employee availability, ensuring workload balance and reducing presenteeism (Johns, 2010), for instance.

When observing through Demerouti et al. (2001)'s lens, organizations' climate of AI acceptance and use can translate as a job resource, as it ensures employees do not feel pressured to work while sick, enabling them to optimize their work after, with the help of AI tools. On the other hand, it enables to lower job demands through automation tasks and decision-making anchoring.

2.5. AI-Driven HR Decision-Making

The application of artificial intelligence in human resource decision-making goes across various domains, including employee evaluation, health-related workplace decisions, and employee performance analysis (Okatta et al., 2024). AI-based tools apply machine learning algorithms to detect workplace trends and provide predictive recommendations (Chowdhury, et. al., 2023), which allow human resource professionals to anticipate challenges such as burnout risks or absenteeism tendencies. Furthermore, according to Brougham and Haar (2018), platforms with AI capabilities analyse historical workforce data, which enables the highlighting of existing correlations between workplace conditions and employee productivity levels, which later inform policy adjustments, for instance.

One key area where AI has demonstrated impact is on recruitment processes. According to Karaboğa et al. (2022), finding the best people for an organization is one of HR's most time-consuming tasks, and AI as a huge potential to increase the hiring cycle's efficiency (Gupta & Kumar, 2024). AI tools can enhance candidate's experience and streamline HR processes. For example, predictive analysis in talent acquisition can forecast the success of potential hires, while in talent retention, it can anticipate employee turnover, enabling proactive engagement

strategies (Kadirov et al., 2024). Likewise, HR experts, are able to make better decisions regarding who has the most probability of succeeding in the company. Also, AI enables HR practitioners to rely on data-driven assessments rather than subjective judgements, thus ensuring diversity and inclusion.

Furthermore, AI supports employee performance and employee engagement, as it can identify workers who could be considering quitting, by monitoring their computer usage and alerting management (Geetha & Reddy, 2018). Also, machine learning algorithms can identify patterns that may indicate high potential or areas needing improvement, enabling more objective assessments (Ployhart & Moliterno, 2011), this happens due to AI's ability to monitor progress in real time and give feedback instantaneously (Aldulaimi et al., 2020). With the help of AI tools, human resource practitioners can make more informed decisions on who to promote or resign, while also detecting more effectively, employees that might need help to better perform.

Regarding training and development, AI can successfully plan, organize, and coordinate training programs for all employees (Aldulaimi et al., 2020), and managers are able to plan training programs and opportunities based on employees' skill gaps. Now-a-days, AI enables employees to pursue career paths efficiently and securely without significant costs, by providing access to databases that contain information about their individual talents and skills.

Furthermore, concerning compensations, with the help of artificial intelligence it is possible to compile lists of wages that help to speed up the evaluation process calculating bonuses according to performance, for instance, contributing to sustain justice in rewarding systems and other types of compensations.

However, AI application in presenteeism remains largely unexplored. One of the primary reasons for this under exploration may be connected to the subjective and highly sensitive nature of presenteeism. Unlike absenteeism, which is a tangible and measurable phenomenon, defined by an employee's physical absence, presenteeism operates within grey areas (Hemp, 2004), requiring nuanced decision-making. Accordingly, employees with any type of illness or health condition may show different levels of ability to work (Kinman, 2019), and AI may struggle to account for the personal, emotional, and situational factors that are influencing the employee's well-being (Hemp, 2004). As an example, and to highlight the complexity of presenteeism-related decisions, two employees with the same chronic condition, such as a migraine, may expose different levels of severity and demonstrate different performance levels and workplace behaviours. Furthermore, an employee with a chronic condition might as well behave or show different levels of illness severity from another employee with a temporary

condition. Accordingly, it also becomes important to understand if AI tools are able to differentiate these health conditions and decide accordingly to what the employee might have to deal with during its workday.

In light of this, as AI is not a human-being, it lacks empathy, ethical reasoning, and contextual understanding, only relying on data-based structures and identifiable patterns, although it might be able to mimic human emotions and transpose a sense of empathy (Booch et al., 2021). Accordingly, this dimension might make AI be perceived, under occupational health decisions, as not trustworthy. According to Booch et al. (2021), “the kind of evidence afforded by the presence of empathy, crucial to making judgments of (un)trustworthiness is conspicuously inaccessible to purely data and pattern-driven AI systems”. Furthermore, knowledge and reasoning-driven AI systems are not at a point that can interpret moral reasons in context (D’Cruz et al., 2022). As showed above, the lack of empathy of AI makes it more difficult to trust its decisions under such sensitive subjects, such as presenteeism. On the other hand, managers might follow AI recommendations without using their own cognitive resources (Bolander, 2019). According to Cecil et al. (2024), managers may be presented with only two different scenarios: either they reject the algorithm more often than human advice, which is known as algorithm aversion, or they tend to adhere to AI-driven advice rather than human given advice, known as algorithmic appreciation. On one hand, the reluctance of individuals to rely on AI-driven advice relies on a general mistrust in intelligent machines or concerns about their ability to handle subjective or emotionally complex decisions. In the latter scenario, under which AI-advice is appreciated and clearly influences decision-making, the tendency is evident in tasks with measurable outcomes that require logical problem solving or in judgments under uncertainty (Bogert et al., 2022). Similarly, research indicates that the more subjective and emotionally loaded the task is, the less likely individuals are to trust AI to make the right decision (Longoni et al., 2019). On the other side, human decision-makers intuitively weight organizational policies (such as work arrangements), leadership styles and ethical considerations, ensuring personalized evaluations that AI-driven may struggle to replicate.

Therefore, this thesis seeks to bridge this research gap by investigating whether AI-generated occupational health recommendations and decisions align with human HR decision-making processes. Considering this, by analysing how AI platforms respond to presenteeism scenarios, and later compared to HR professionals’ decisions, the present investigation will be able to determine the extent to which AI can be effectively integrated into presenteeism management without compromising employee-centred decision-making. Finally, comparing

both agents on decision-making will reveal whether AI aligns with subjective, ethical, and personalized HR decision-making.

2.6. Augmenting presenteeism decision making

Studying the behaviour of AI tools under presenteeism decision-making processes requires more than a surface-level analysis of their outputs but implies a deeper exploration into the cognitive architecture which lies under decision-making. Accordingly, understanding how these tools operate entails a broader inquiry into the nature of judgment, the structure of thought and the boundaries between human and artificial cognition. Examining the mechanisms through which AI systems generate responses invites comparison with established psychological models of human reasoning, which shed light on the extent to which these technologies replicate, diverge from, or simplify the complexity of human decision-making.

Accordingly, the Dual-Process Theory, widely recognized in cognitive psychology (Chaiken & Trope, 1999; Sherman et al., 2014; Gawronski et al., 2024), contributes immensely to the effective comparison between both AI and human decision-making processes on presenteeism. This model divides thought into two different yet interactive systems: experiential and rational. The experiential system (or intuitive), as described by Epstein (1994), operates automatically and effortlessly, being guided by associative connections and affective principles such as pleasure and pain. In fact, it perceives reality through concrete images, metaphors and narratives, which results in holistic and context specific responses that are often schematic and emotionally charged, tending to be shaped by accumulated experience, evolving over time. On the other hand, the rational system (or analytical) is often characterized by intentional, effortful processing based on logical ligations and abstract symbols. Having this in mind, it encodes reality through words, numbers, and conceptual representations, reflecting responses that are analytically coherent, context-independent and oriented toward delayed action. Changes in this system occur more rapidly and are driven by the strength of arguments and the availability of new evidence.

Rooted in the work of Epstein (1994), Kahneman (2003) later expanded this model distinguishing between System 1, which is fast, automatic, associative and emotionally influenced, and System 2, which is slow, deliberate, rule-governed and emotionally neutral. Both systems can be activated by verbal and conceptual informational, making them highly relevant to organizational decision-making contexts.

In light of this cognitive model, the comparison between generative AI tools and HR managers in presenteeism scenarios can be interpreted as a contrast between agents dominated

by Systems 2 logic and those capable of integrating both systems. Considering this, it is expected that AI generative tools produce outputs that reflect greater System 2 cognitive responses (rule-governed and emotionally neutral) while HR managers, as human beings are expected to reflect responses that perfectly reflect the link between System 1 and System 2 cognitive processes.

However, the analysis of processes behind decisions alone does not fully capture the relational dynamic at play when AI tools are introduced into decision-making tasks. For the present study, it also becomes interesting to understand the leadership styles that these tools simulate through their language and tone, as they are put in the manager's position under the different scenarios. Considering this, the Transformational versus Transactional Leadership Theory, proposed by Judge and Piccolo (2004) enables to classify the AI tools according to the style of leadership they implicitly enact. In fact, the tools that deliver structured, rule-based and compliance-oriented responses reflect a transactional orientation, which emphasizes operational clarity and adherence to standards (Bass & Avolio, 1993). On the other side, tools that incorporate more empathetic phrasing, conditional reasoning, and references to emotional or environmental, dynamic reflect a more transformational orientation, characterized by individualized stimulation and motivational framing (Lowe et al., 1996).

This analysis gains greater importance as it influences the way AI tools are perceived and trusted by humans. Research on algorithmic aversion and appreciation (Cecil et al., 2024; Logg et al., 2019; Mahmud et al., 2022) suggests that the way AI tools respond and reflect their outputs influences user acceptance. AI tools that follow a transactional style, may appear as rigid, impersonal or overly procedural, which is more likely to provoke scepticism or resistance among HR managers, especially in contexts perceived as subjective and sensitive. On the other side, AI tools which reflect a more transformational behaviour may foster greater trust and openness, as their outputs resonate more closely with the relational and adaptative expectations embedded in HR practices. In light of this, the behaviour reflected by AI tools may serve as a mediating factor between algorithmic reasoning and human reception or acceptability of AI tools. It shapes not only the content of the decisions while also their perceived legitimacy, emotional resonance, and alignment.

By integrating both the Dual-Process Theory and the Transactional versus Transformational Leadership Theory it is possible to provide the present study with the comprehensive framework for understanding the behavioural and relational dimensions of AI decision-making. In fact, it makes possible to move beyond by considering how AI tools communicate their rationality, and essential consideration for their responsible integration into organizations.

Understanding how AI tools think and what behaviours do they reassemble is critical to help anticipating their impact in organizational decision-making settings. Also, by identifying A's type of reasoning and behaviours, it is possible to identify differences and gaps when compared with human decision-making under highly sensitive scenarios, such as decision making. This helps to frame the findings to the final research question, based on the differences between the two agents on decision-making processes.

3. RESEARCH PROPOSAL

The present research becomes crucial to augment knowledge on presenteeism literature, helping to delve deeper into understanding how artificial intelligence is able to amplify manager's presenteeism-driven decisions.

While presenteeism has been extensively studied in terms of its impact on predictive analytics, performance insights, recruitment efficiency and employee well-being (Jia et al., 2023), there remains a significant gap in understanding how AI tools engage in presenteeism decisions. This investigation seeks to address that gap by evaluating AI tools' decision behaviours in interpreting and evaluating contextual variations on presenteeism, while aiming to better comprehend how these tools mirror or complement human reasoning.

The eight presenteeism scenarios used in the present study were designed to reflect the full range of contextual combinations. Rather than isolating individual factors, the study adopts a factorial approach which enables to captures the intersections between different variables, recognizing that presenteeism decisions rarely occur in isolation but are shaped by overlapping organizational dynamic as well. Having this into consideration, this scenario design allows for a comprehensive exploration of how different configurations of health conditions, workplace attendance flexibility and technological support influence judgments about attendance. Accordingly, the scenarios presented reflect realistic dilemmas grounded in the literature previously explored. According to Johns (2010), "work context factors influence the choice of presenteeism, and strict attendance policies tend to favour the occurrence of presenteeism", and on the same tone, Miraglia & Johns (2016), highlight that stricter absence policies were associated with higher presence despite illness. Furthermore, the meta-analysis proposed by the ladder authors shows that the general health status is negatively associated with working when ill and that a supportive workplace (such as allowing employees to use different tools and means to get their tasks done), decreases the probability of going to work despite ill. By embedding these dynamics into the scenario structure, the present study findings are shielded with established theoretical insights and contributes to expansion of presenteeism decision-making literature.

Accordingly, the present research provides theoretical and practical insights for artificial intelligence decision-making process through the lens of leadership styles and cognitive processing models, offering a deeper understanding of which leadership style to these tools reflect, and the cognitive processing behind the decisions taken. By using various contextual

dimensions and comparing different hypothetical situations, the present study is able to contribute for presenteeism literature by reframing presenteeism not only as a behavioural act, such a going to work while ill (Hemp, 2004; Karanika-Murray & Cooper, 2018) but also as a multidimensional decision shaped by individual perception and organizational flexibility. Furthermore, the study highlights the limitations of AI tools when operating in subjective, context-dependent environments, where human intuition and experiential judgment often play a critical role.

Practically, the investigation compares multiple generative AI systems to identify differences in their decision logic, communicative framing, and alignment with human cognitive patterns. Given the growing availability of AI tools with similar generative capabilities, it becomes essential to evaluate which systems are best suited to support managerial decision-making in presenteeism contexts and to determine their reliability as anchors for organizational decision-making.

Having this in mind, the present study aims contribute to presenteeism's academic literature by providing answers to three different research questions:

1. Is the variation between HR managers' and algorithms' evaluations of presenteeism scenarios equal?
2. Do both algorithms and HR managers differentiate between different presenteeism scenarios?
3. Are there are differences between evaluations given by algorithms and HR managers?

4. METHODOLOGY

4.1. Sample

The participant sample (Annex A) consists of 119 human resource managers, all Portuguese, being 79,8% female (95 participants) and 20.2% male (24 participants). It is a relatively young sample, as the mean age is 38,13 years.

Regarding for how long the participants have been HR managers, on average, the participants are on the same position for 3,91 years. Moreover, 41,2% are on the same position from one to three years (49 participants), while only 9,1% admit they have been HR managers from seven to nine years. Furthermore, 39,5% of participants work inside the Services sector, while 26,1% work inside the Technology sector and 19,3% on other fields of the market.

4.2. Procedure

The present study employed a scenario-based comparative design to investigate how human resource managers and generative intelligence tools evaluate presenteeism-related situations.

Having this in mind, eight hypothetical workplace scenarios were developed using a situational judgement test (SJT) methodology which is commonly applied in professional and academic contexts, in order to assess a wide range of competencies, such as interpersonal skills, professionalism, and ethical reasoning (Corstjens et al., 2017; Lievens & Patterson, 2011; Patterson et al., 2016). As such, this tool can take a variety of forms, but generally presents applicants with a series of contextualized scenarios, either written (i.e. multiple options, ranking from best to worse) or via a short video, and ask them what they would (or in some cases should) do in that situation (Hardwood et al., 2024). Furthermore, and unlike traditional assessments, which are solely focused on cognitive abilities or knowledge, SJTs aim to evaluate participants' behavioral tendency and have, therefore, demonstrated both reliability and validity in selection and admission contexts (Corstjens et al., 2017), which makes them popular specially in medical programs. When in comparison to more cognitively loaded selection methods, SJTs have less impact on equity, diversity, and inclusion variables, offering one of the best validity-diversity trade-offs amongst selection tools (Lievens et al., 2016; Ployhart & Holtz, 2008).

Under the present research, each scenario described a unique occupational health dilemma involving an employee upon which the manager decides whether to attend work under a range of health, organizational, and contextual conditions. Participants in the human group consisted of HR managers, each of whom responded to all eight scenarios in the same order. Each

participant was asked to rate the appropriateness of the employee attending work in the given situation on a standardized scale and to provide a brief written justification for their ratings. Likewise, the same eight scenarios were also used as prompts for five generative tools. Each scenario was input as a prompt into each AI tool, eight times in a randomized order, which allowed for a direct comparison of not only the average rating generated by each AI tool but also their internal consistency and reasoning across multiple insertions of the same scenario.

For the HR managers, since it was important for the participants to clearly understand the differences and conditions of each, the scenarios were translated and distributed into their native language, Portuguese, creating a different version of the original scenarios in English, applied to the AI tools. By translating, the purpose relied on avoiding any form of foreign language effect, that could have distorted participants' perception of the target health and company's policies conditions (Costa et al., 2014). The scenarios for the different AI tools were prompted in English to ensure better results, as their capabilities and comprehensive skills are augmented in the language they were originally programmed and tested in.

4.3. Instruments

4.3.1. Situational judgment tests

The primary instrument used in this research was a set of eight situational judgment test scenarios, specifically designed to represent common presenteeism situations found in the workplace.

For each scenario, raters were responsible for evaluating the employee's eligibility for health-related accommodations, having in mind the three study variables: the nature of the health condition (chronic or temporary), remote work policy (remote work allowed or remote work not allowed) and the organization's artificial intelligence acceptance climate (AI tools accepted or AI tools not accepted). Annex B shows how each scenario was presented to the respondents.

The eight scenarios included the variables as follows:

- Scenario 1: Chronic Health Condition; AI use not accepted; Remote Work is not allowed;
- Scenario 2: Temporary Health Condition; AI use not accepted; Remote Work is allowed;
- Scenario 3: Chronic Health Condition; AI use accepted; Remote Work allowed;
- Scenario 4: Temporary Health Condition; AI use accepted; Remote Work allowed;
- Scenario 5: Chronic Health Condition; AI use not accepted; Remote Work allowed;

- Scenario 6: Temporary Health Condition; AI use not accepted; Remote Work not allowed;
- Scenario 7: Chronic Health Condition; AI use accepted; Remote Work not allowed;
- Scenario 8: Temporary Health Condition; AI use accepted; Remote Work not allowed;

Regarding the setting of the scenarios, a fictional employee was created and a fictitious name, *Noah*, was given, to avoid any preconceptions (i.e.: gender) during the assessment. Noah has worked in the company for some years, his employment history indicates a strong work ethic with no recent significant performance issues and skill-wise, Noah has acceptable technical and interpersonal skills. It is worth noting that the type of health conditions (chronic or temporary) were always accompanied by a specification of the illness (back pain and allergies, respectively) in appraisal of health conditions, in order to prevent individual subjective differences (Biswas et al., 2009), as some participants might consider different illnesses for each type of condition or even consider a specific illness as chronic when other might consider as temporary.

The responses were gathered for both quantitative and qualitative analysis through ratings and justifications, respectively. For the quantitative analysis, for each scenario, HR managers and AI tools were asked to rate the appropriateness of the employee attending work using a 6-point Likert Scale, in which 1 (*the employee should definitely not go to the office*) and 6 (*the employee should definitely go to office*). This scale contains six items instead of seven to avoid neutral responses and thus, central tendency effects on decision ratings. These ratings served as the basis for the statistical comparison of decisions and variance across both human and AI raters. For the qualitative analysis, both human participants and generative intelligence tools were asked to provide short justifications for their ratings, which were later subjected to thematic and discourse analysis to explore differences in tone, reasoning, and contextual sensitivity.

4.3.2. Generative intelligence tools

The different generative intelligence tools explored under the presented study were carefully chosen based on their widespread public availability, prevalence under professional and personal use, and relevance within the current technological landscape.

Firstly, ChatGPT, created by OpenAI, was considered important for the present research due to its pioneering role in public-facing generative AI. As the first widely adopted conversational agent, ChatGPT became a reference point for both individual and organizational use (Stefanelli, 2025). According to the same author, this generative intelligence tool holds the

largest market share in generative AI usage (60.5%) and is used by 92% of Fortune 100 companies.

Microsoft Copilot was selected due to its deep integration within the Microsoft 365 ecosystem, which is widely adopted across organizational environments (Microsoft, 2024). According to Microsoft (2024), it leverages OpenAI's GPT-4 foundational Language Learning Model (LLM), and is the second most used generative intelligence tool. Furthermore, a Wharton's survey published in 2024 on generative intelligence usage, demonstrated that 52% of respondents admitted currently usage of Microsoft Copilot, while 35% of respondents were testing and trying to implement in their daily lives. Its popularity among organizations lies in its integration with the productivity apps employees in Microsoft environments use (Korst et al., 2024). On the same note, Gemini, developed by Google, represents one of the most widely accessible and publicly recognized AI platforms due to its integration into Google Workplace and Android systems, commonly used among individuals and organizations (Korst et al., 2024).

On a different level, Grok, developed by Elon Musk, was chosen to integrate the present research for its distinctive personality-driven design and real time data processing capabilities (Olavsrud, 2025). Its recent growth, reaching over 20 million monthly active users, signals its emerging relevance under consumer settings (Perez, 2025).

Finally, ChatBOX, although not so commonly used among individual users or inside organizational contexts (Olavsrud, 2025), it was included in the present research intentionally and strategically. While its technical capabilities are comparable to mainstream generative intelligence tools, its adoption remains relatively limited. Its lower market penetration presents a valuable opportunity to contrast its decision-making capabilities with that of more widely used generative intelligence tools, as the ones mentioned and chose for the research.

Having this in mind, the present group of generative intelligence tools ensures validity to the procedure and findings, as the tools are representative of those that HR managers are most likely to encounter or interact with in real-life organizational scenarios, or work as a contrasting factor for better understanding generative intelligence tools' decision behaviours.

4.4. Variable measures

In each scenario, three different variables were used, according to their influence on presenteeism decisions, as not only the symptoms, but also the organization's policies have an impact on presenteeism.

The variable *Health Condition* draws on research showing that the type and perceived severity of a health condition is one of the strongest predictors of presenteeism, even more so

than absenteeism (Aronsson & Gustafsson, 2005). In fact, various health conditions are frequently related with high presenteeism rates, as for instance, headaches, allergies, asthma, or dermatitis (Martinez & Ferreira, 2011). While chronic conditions often involve ongoing management and invisible symptoms, which can lead to underestimation of their impact, temporary health conditions also are more likely to be seen as short-term disruptions (Hemp, 2004), and thus belittled. The *Health Condition* variable plays a crucial role in highlighting how health conditions directly influence the decision on the employee's attendance to work. In the present study, the variable is measured on a binary scale, being distinguished between *chronic* (which requires ongoing monitoring and management) and *temporary* (which requires short-term adjustments).

Furthermore, work arrangements also play a big role as they reflect the organization's culture and policies, which are known to influence attendance decisions (Ruhle et al., 2019). Theoretical models, like the JD-R model (Bakker & Demerouti, 2007) suggest that when employees have access to resources like remote work, they are better able to manage health and productivity. The presence of the variable *Remote Work Policy* helps to understand the organization's flexibility in allowing employees to work remotely, and it becomes crucial to assess how work flexibility arrangements influence health needs and impact presenteeism-decisions. This variable is measured on a binary scale, distinguished as either *allowed* (when the employees are able to stay at home while continuing to perform their tasks) or *not allowed* (when work is solely performed on site).

Additionally, workforce behaviors are being shaped by the increasing integration of digital tools in organizations. For instance, the organization's level of acceptance of artificial intelligence tools represents organization's openness to evolution and employee well-being, and consequently, influences how employees perceive support, autonomy, and workload management, while also enabling them to develop their tasks more effectively. For instance, AI-powered collaboration tools, such as virtual spaces, allow employees to develop their work outside of the office, contributing to reduce presenteeism rates (Bailey & Kurland, 2002), while generative intelligence tools may help them organize or structure better their daily tasks. Knowing this, including the organization's level of acceptance and use of AI is important as it influences how employees manage their health and productivity. In workplaces that embrace AI, employees often have access to tools that support flexible work, reduce pressure to be physically present and help maintain performance even when unwell. Conversely, low AI acceptance can reinforce rigid attendance norms, increasing presenteeism and its negative effects. Having this in mind, the *AI Acceptance Climate* variable helps to identify the readiness

and support of the organizations for adopting artificial intelligence tools, being presented in a binary scale, categorized as *accepted* (when the organization provides its employees with AI tools to help them perform their tasks) or *not accepted* (when there are no AI tools available inside the organization and thus, cannot be used to perform tasks).

5. RESULTS

All the statistical analyses throughout this research project were carried out using SPSS Version 29 software. As the samples are relatively large, confidence level intervals were set at 95%, meaning that a p -value lower than 0.05 was considered statistically significant.

5.1. Descriptive Analysis

Table 5.1 shows the mean ratings for each scenario given reflect the decisions of both HR managers and each generative intelligence tool on different presenteeism contexts.

Table 5.1

Descriptive statistics of the study variables.

		<i>M</i>	<i>SD</i>
Scenario	1	3.03	1.514
	2	2.12	1.098
	3	1.87	1.115
	4	2.00	1.080
	5	2.34	1.019
	6	3.30	1.577
	7	3.14	1.421
	8	3.35	1.575

Having all raters into consideration, mean ratings ranged from 1.87 to 3.35 on a 6-point Likert Scale where, the higher the values, the greater the propensity to decide that the employee should go to work, in which 1 (*the employee should stay at home*) while 6 (*the employee should definitely go to work*).

Firstly, scenarios two, three, and four received the lowest overall rating: $M_{\text{scenario 2}}=2.12$, $SD_{\text{scenario 2}}=1.098$, $M_{\text{scenario 3}}=1.87$, $SD_{\text{scenario 3}}=1.115$, $M_{\text{scenario 4}}=2.00$, $SD_{\text{scenario 4}}=1.080$. This indicates that these scenarios were the ones where there was a higher probability that the employee should stay at home, having in mind the health condition and organization's acceptance of AI and remote work. Under the second scenario the health condition was temporary, AI use was not allowed while remote work was accepted, while under the third scenario the health condition was chronic, and both AI and remote work were accepted, and

under the fourth scenario the health condition was temporary, and both AI and remote work were accepted. Contrarily, under the scenarios six, seven and eight the mean ratings were the highest: $M_{\text{scenario 6}}=3.30$, $SD_{\text{scenario 6}}=1.577$, $M_{\text{scenario 7}}=3.14$, $SD_{\text{scenario 7}}=1.421$, $M_{\text{scenario 8}}=3.35$, $SD_{\text{scenario 8}}=1.575$. This reflects a tendency to decide that the employee should go to work. Under the sixth scenario the health condition was temporary, and neither AI or remote work were allowed, while under the seventh scenario the health condition was chronic, AI use was allowed but remote work was not, and under the eighth scenario the health condition was temporary, AI use was also allowed while remote work was not. Subsequently, all other presenteeism scenarios fell in between, reflecting more moderate evaluation of the circumstances presented. Finally, standard deviations across scenarios revealed moderate dispersion, ranging from 1.0 to 1.6, indicating some degree of disagreement among respondents.

Table 5.2

Descriptive statistics of the study variables.

		HR Manager		ChatBOX		ChatGPT		Gemini		Microsoft Copilot		Grok	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Scenario	1	3.23	1.539	2.17	0.408	2.83	.408	2.83	.408	1.00	.000	2.83	1.835
	2	2.03	1.030	1.33	.816	2.00	.000	1.67	.516	3.00	.000	3.33	1.506
	3	1.80	1.064	1.17	.408	2.17	.408	1.67	.516	1.33	.816	3.33	1.862
	4	1.89	.986	1.00	.000	2.00	.000	1.67	.516	3.00	.000	3.17	1.835
	5	2.29	1.071	2.00	1.095	2.50	.548	2.50	1.225	2.00	.000	3.00	.894
	6	3.42	1.722	2.00	.000	4.67	.516	3.00	.000	4.00	.000	1.67	.816
	7	3.23	1.579	2.33	.516	4.00	.000	3.17	.408	2.00	.000	2.83	1.472
	8	3.38	1.674	2.17	.408	4.67	.516	3.33	0.816	3.00	1.095	3.00	2.191

Table 5.2 shows the mean ratings distinguished by respondent. On one side, HR managers displayed the most variability both in terms of overall judgement and internal consensus. For instance, the mean ratings ranged from 1.80 in scenario three to 3.42 under scenario six, with standard deviations reaching 1.722. This reflects considerable divergence in individual evaluations. On the other side, generative intelligence tools produced a more tightly clustered mean scores, as their evaluations tended to fall within a narrow band, with standard deviations frequently below 0.600. In fact, in some specific cases the given ratings were completely uniform, as it is the case of Microsoft Copilot's null standard deviation across various scenarios except for scenarios three (chronic health condition; AI use accepted; remote work allowed) and eight (temporary health condition; AI use accepted; remote work not allowed). Despite this trend of almost null standard deviation, Grok notably distinguished itself from the other generative intelligence tools, as the ratings were not only higher in many of the scenarios: $M_{\text{scenario 3}}=3.33$, but were also followed by large standard deviation values: $SD_{\text{scenario 8}}=2.191$.

5.2. Interaction of scenarios and respondents on ratings

To understand how participant's ratings varied across the different presenteeism scenarios, and to investigate whether those variations depended on the group of rater (HR vs. Generative Intelligence tool), a repeated measures ANOVA was conducted. While the main effect tests whether the eight scenarios were rated differently on average, regardless of who was rating them, the interaction level examines whether those differences in scenario ratings varied by group of respondents.

To solidify this idea, and to understand how specific respondent types vary in their interpretation of presenteeism contexts, the interaction between scenario and each respondent type was analysed (Annex D). This model reveals that the pattern of ratings across scenarios varied significantly between the six raters' type: HR, ChatBOX, ChatGPT, Gemini, Microsoft Copilot and Grok. The interaction effect was statistically significant across all tests: Pillai's Trace = 0.691, $F(35;435) = 1.992, p < 0.001$, Wilk's Lambda = 0.450, $F(35;351,579) = 2.099, p < 0.001$, Hotelling's Trace = 0.933, $F(35;407) = 2.170, p < 0.001$, Roy's Largest Root = 0.435, $F(7;87) = 5.402, p < 0.001$. Furthermore, a moderate to large interaction effect is suggested: partial $\eta^2_{\text{Pillai's Trace}} = 0.138$, partial $\eta^2_{\text{Wilk's Lambda}} = 0.148$, partial $\eta^2_{\text{Hotelling's Trace}} = 0.157$, partial $\eta^2_{\text{Roy's Largest Root}} = 0.303$. This explains and solidifies the idea that each respondent type applied a different pattern of reasoning or values when evaluating the same scenarios and thus, not all scenarios are judged and though rated equally.

Additionally, to identify where the differences were, pairwise comparisons were conducted (Annex D). The first scenario describes a presenteeism context under which the employee's health condition is chronic, the organization does not support AI use nor working from home, while the third scenario describes a presenteeism context where the employee's health condition is also chronic but both AI and remote work are supported by the organization. Under these circumstances, the first scenario was rated significantly higher than scenario three, reflecting the pairwise comparison to logically indicate a significant statistically difference in ratings: $M_{\text{scenario 1}} = 3.03, M_{\text{scenario 3}} = 1.87$. These results lead into the conclusion that the context of first scenario might be perceived as the one with the highest probability that employee should go to work, although under both scenarios, the employee presents a chronic condition. This leads to the conclusion that, even with a chronic health condition, when the employee does not have the support to work from home and maintain tasks with the help of AI, it is likely that the respondents decide that the employee should go to work. On the other side, when the support tools are given, the decision will likely be for the employee to stay at home and recover.

The Post Hoc comparisons revealed significant differences in ratings, particularly across scenarios two and six, and also between seven and eight, which only differ in the allowance of remote work (scenario two: temporary health condition; AI not accepted; remote work allowed; scenario six: temporary health condition; AI not accepted; remote work not allowed)

The mean difference in ratings is significant ($p < 0.05$) when scenarios only differ in work regime, which happens with the relationships between scenarios two and six = -0.897 (SE = 0.232, 95% CI = -1.358, -0.437), scenarios three and seven = -1.016, (SE = 0.237, 95% CI = -1.487, -0.545), and scenarios four and eight = -1.138, (SE = 0.261, 95% CI = -1.656, -0.620). Furthermore, if the scenarios differ in at least the work regime, the more likely it is for the ratings to be significantly different: MD_{scenarios 2 and 8} = -1.031 (SE = 0.265, 95% CI = -1.558, -0.504), MD_{scenarios 3 and 6} = -1.214 (SE = 0.238, 95% CI = -1.686, -0.741), MD_{scenarios 3 and 7} = -1.016 (SE = 0.237, 95% CI = -1.487, -0.545), MD_{scenarios 3 and 8} = -1.347 (SE = 0.256, 95% CI = -1.856, -0.839), MD_{scenarios 4 and 6} = -1.004 (SE = 0.214, 95% CI = -1.428, -0.579), MD_{scenarios 4 and 8} = -1.138 (SE = 0.261, 95% CI = -1.656, -0.620). This explains that the work regime has the greatest impact on ratings and, consequently, on decisions. In fact, the tendency to decide for the employee to stay at home is greater when remote work is allowed ($M_{\text{scenario 2}} = 2.12$, $M_{\text{scenario 3}} = 1.87$, $M_{\text{scenario 4}} = 2.00$, $M_{\text{scenario 5}} = 2.34$) compared to when it is not ($M_{\text{scenario 1}} = 3.03$, $M_{\text{scenario 6}} = 3.30$, $M_{\text{scenario 7}} = 3.14$, $M_{\text{scenario 8}} = 3.35$). The same significant mean difference does not happen when the difference relies on AI acceptance or health condition ($p > 0.05$).

When analysing the pairwise comparisons overall, it becomes evident that scenarios seven and eight are consistently significantly statistically different from all the other scenarios, excepting scenario six (all $p < 0.05$). Furthermore, when comparing the mean ratings, these three scenarios have the highest values, reflecting that they probably stand out for being less severe on the employee's conditions. However, when analysing the conditions of the three, in all of them, there is no possibility of working from home, which may justify why the ratings are higher: if the employee does not have the possibility to stay at home to work, there is a highest chance that the respondent induces the employee to go to work. Having this in mind, the variable work regime seems to have the biggest impact on allowing the employee to go to work.

However, there is scenario one (chronic health condition; AI not accepted; remote work not allowed), under which remote work is also not accepted and still presented a significant statistical difference when compared with scenarios sixth, seventh and eighth. When analysing the mean ratings, scenario one also has the highest values, similarly to those given to scenarios six, seven and eight ($M > 3.00$). Although the mean ratings for scenarios one ($M = 3.03$), six ($M = 3.30$), seven ($M = 3.14$) and eight ($M = 3.35$) were relatively close, the

differences were statistically significant. This is explained by the within-subject design of the study: the same respondents evaluated all scenarios, which reduces error variance and increases the sensitivity of the analysis. Even small and consistent differences in how participants rated these scenarios can therefore lead to statistically significant results.

Furthermore, varying degrees of alignment between human resource managers and generative intelligence tools were found across the eight scenarios (Annex D). While most tools exhibited no significant statistical differences ($p > 0.05$), suggesting general convergence with human evaluators, three specific comparisons reached statistical significance ($p < 0.05$). Microsoft Copilot differed significantly from HR managers under scenario one (MD = 2.230, (SE = 0.591, 95% CI = 0.450, 4.010)), suggesting also more lenient judgments relatively to HR managers under a chronic illness and low organizational flexibility. Grok, on the other hand, showed consistent divergence in scenarios two, three, and four, with significant mean differences: MD_{scenario 2} = 1.300, (SE = 0.414, 95% CI = -2.550, -0.050), MD_{scenario 3} = -1.530, (SE = 0.443, 95% CI = -2.870, -0.200), MD_{scenario 4} = -1.270, (SE = 0.406, 95% CI = -2.500, -0.05). These results imply that Grok's ratings were notably stricter when health condition was temporary and remote work or AI support varied. Contrarily, ChatBOX, ChatGPT and Microsoft Copilot were the ones with major non-significant results ($p = 1.000$), indicating high similarity to human judgement.

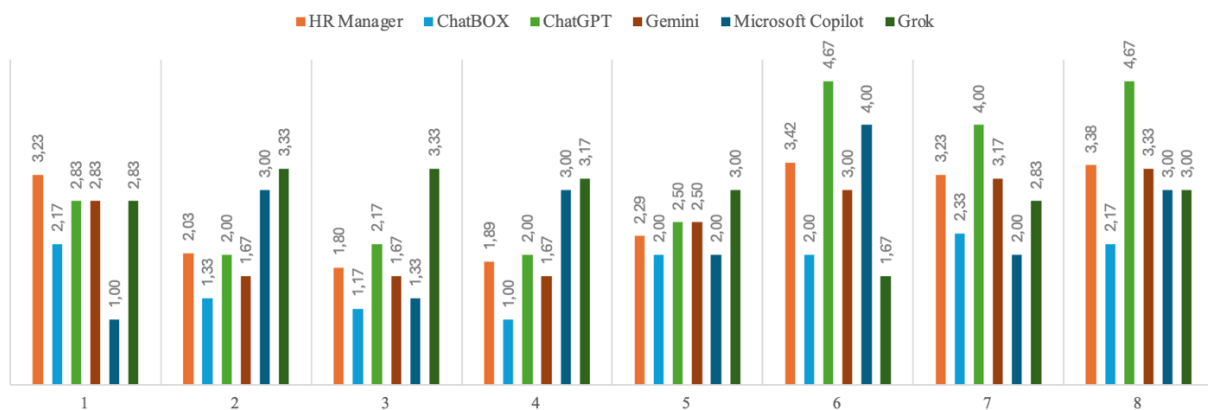


Figure 5.1 *Leniency and Strictness of raters across scenarios.*

Finally, Figure 5.1 shows, on a broader view, the analysis of the average ratings reveals patterns in decisions across scenarios. ChatBOX was the most consistently lenient, recommending staying at home in five out of eight scenarios. Microsoft Copilot was also significantly lenient under scenario one (chronic health condition; AI use not accepted; remote

work not allowed), and Grok under scenario 6 (temporary health condition; AI use not accepted; remote work not allowed). On the contrary, ChatGPT and Grok emerge as the strictest tools, rarely recommending the employee to definitely stay at home, especially when remote work was unavailable. ChatGPT was strictest in scenarios six (temporary health condition; AI use not accepted; remote work not allowed), seven (chronic health condition; AI use allowed; remote work not allowed) and eight (temporary health condition; AI use accepted; remote work not allowed), while Grok leaned toward stricter decisions under scenarios two to five, although in all of them, remote work was allowed. Lastly, HR managers were also strict under scenario one, reflecting possible organizational policy-based decisions, and these raters were never the most lenient under each scenario.

5.3. Variance Analysis

Table 5.3 shows the degree of disagreement among respondents, having in consideration all the eight different presenteeism scenarios.

Table 5.3

Variance by respondent.

		Variance					
		HR Managers	Gen AI Tool				
			ChatBox	ChatGPT	Gemini	Microsoft Copilot	Grok
Scenario	1	2.485	.167	.167	.167	.000	3.367
	2	1.225	.667	.000	.267	.000	2.267
	3	1.170	.167	.167	.267	.667	3.467
	4	1.100	.000	.000	.267	.000	3.367
	5	1.158	1.200	.300	1.500	.000	.000
	6	2.922	.000	.267	.000	.000	.667
	7	2.472	.267	.000	.167	.000	2.167
	8	2.759	.167	.267	.667	1.200	4.800

When analysing HR managers results, across all scenarios, this group consistently showed the highest levels of variance, with values ranging from scenario four ($\sigma^2_{\text{scenario 4}} = 1.100$) to scenario six ($\sigma^2_{\text{scenario 6}} = 2.922$) that had less agreement and thus more heterogeneity in ratings. Accordingly, these results suggest substantial heterogeneity in how HR managers interpreted and rated the eight different presenteeism scenarios.

Contrarily, all the generative intelligence tools, except Grok, demonstrated consistently low rating variance across most scenarios. In many cases, these tools returned null variance, such

as Microsoft Copilot under all the scenarios excepting the third, fourth and eight, or ChatGPT and Gemini under the fourth. This uniformization of the given ratings suggests a high level of internal consistency in how these platforms generate judgement, likely due to standardized language models, constrained output structures and tightly controlled prompts.

Curiously, among the generative AI tools, Grok's behaviour diverged substantially, as this tool exhibited severe higher variances in half of the scenarios: $\sigma^2_{\text{scenario 1}} = 3.367$, $\sigma^2_{\text{scenario 3}} = 3.467$, $\sigma^2_{\text{scenario 4}} = 3.367$, $\sigma^2_{\text{scenario 8}} = 4.800$. Surprisingly, Grok's rating decisions were in some cases even more variable than the HR managers, especially under scenario eight, which may indicate a less constrained model design, which a different foundation from all the other generative AI tools.

5.4. Qualitative analysis

The justifications of the ratings generated by the five different generative intelligence tools reflect a consensus on the importance of prioritizing health in the context of presenteeism, but they do differ in tone, reasoning, and communication style. All tools consistently give emphasis to prioritize health and staying at home when health is compromised, while acknowledging the importance of giving use of remote work as a viable solution (Annex E).

Across scenarios, ChatBOX tends to be concise and assertive, issuing direct, health-centred recommendations with minimal elaboration. Its responses are short and to the point, often framed as gentle imperatives or firm suggestions that avoid excessive detail: *"Given your chronic health condition that requires regular management and the lack of support for AI-based tools in your organization, it may be better to prioritize your health over attending the office."* [ChatBOX] under scenario one, or *"Since remote work is permitted and you have a temporary health condition that can be managed from home, it would be wise to take advantage of the remote work option to focus on your recovery."* [ChatBOX] under the second scenario. ChatGPT and Gemini take a more contemplative tone, offering conditional reasoning that balances health concerns with professional responsibilities. Accordingly, their language is more measured, often introducing conditional statements *"If working remotely enhances your ability to manage your health condition, it makes sense to take advantage of this option"* [ChatGPT] (see Annex E, Scenario 2) or *"If your condition significantly impacts your ability to work effectively or poses a risk to your health, prioritize your recovery"* [Gemini] (see Annex E, Scenario 6) , or suggesting conversations with management to accommodate nuanced circumstances, for instance under scenario six *"However, if there's any risk to your health, it's worth discussing accommodations with your organization."* [ChatGPT] or *"If possible, discuss*

your situation with your manager. Explain your condition and explore whether any alternative arrangements (e.g., flexible start/end times, reduced hours) might be possible.” [Gemini] (see Annex E, Scenario 6). On another note, Microsoft Copilot blends its reasoning with empathetic phrasing, often explicitly acknowledging emotional dimensions such as stress *“This way, you can manage your health condition effectively without the added stress of commuting and being in the office”* [Microsoft Copilot] (see Annex E, Scenario 3) discomfort, or well-being *“Your health and well-being should always come first”* [Microsoft Copilot], under the first scenario. Its responses tend to be warmly encouraging, often embedding supportive statements about employee care *“Prioritizing your recovery is important, and working from home will allow you to take care of yourself better”* [Microsoft Copilot], under the fifth scenario, for instance.

Curiously, once again, Grok stands out from all the other generative intelligence tools, delivering the most expressive responses. Accordingly, its phrasing is almost conversationally human, and its logic has layers. Having this in mind, it goes beyond, considering environmental stressors and organizational culture *“Given the organization's lack of support for AI-based tools and the skepticism among employees, I think it's likely that you'll face additional stress and challenges in the office environment”* [Grok] (see Annex E, Scenario 1), and anticipating emotional challenges *“I think it's a great chance to take care of yourself and prioritize your health without having to worry about commuting or navigating an office environment that may not be conducive to your needs”* [Grok] (see Annex E, Scenario 2), becoming the only tool that consistently brings elements like “commuting strain” or “workplace scepticism”, which suggests a higher level of context awareness (or at least, better mimic abilities). Lastly, Grok’s suggestion under the second scenario, greatly represents the flexibility its algorithm provides in its recommendations, reflecting more fluent and human-like responses *“Given the organization's acceptance of remote work, I think it's a great chance to take care of yourself and prioritize your health without having to worry about commuting or navigating an office environment that may not be conducive to your needs. Considering your temporary health condition, I would recommend taking advantage of the remote work option to recover and manage your health. This will likely help you recover faster and more effectively, and you can always discuss your situation with your employer to ensure a smooth transition back to the office when you're feeling better”* [Grok].

5.5. The dualities of algorithmic behaviour based on leadership style and cognitive reasoning

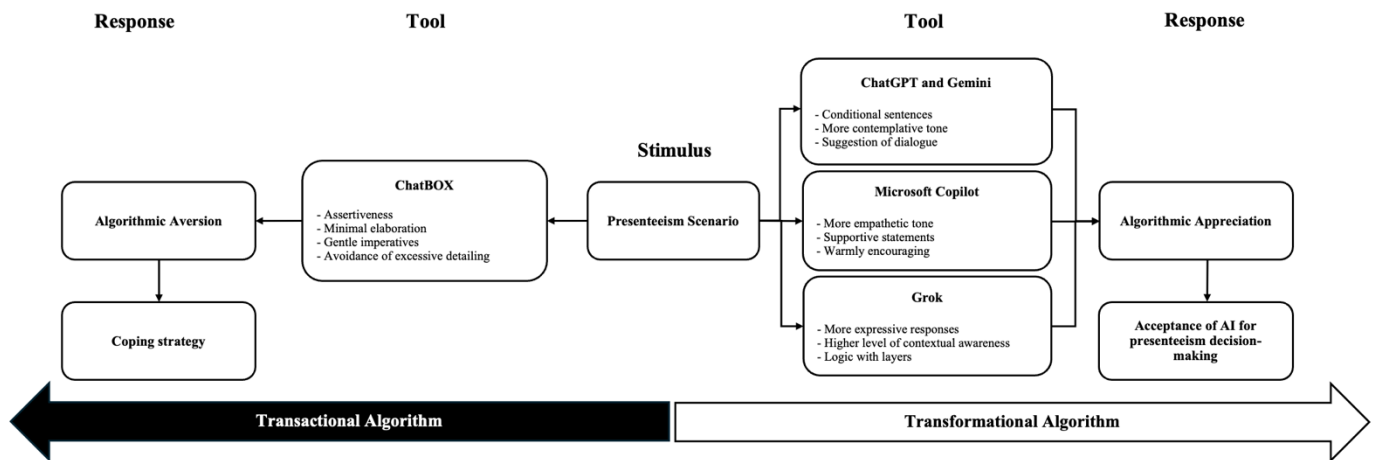


Figure 5.2 Proposed framework for the transactional versus transformational duality of algorithms.

By analysing the decision behaviours and justifications, it becomes possible to distribute each generative intelligence tool considering its more transactional or transformative algorithm (Figure 5.2), adapting the leadership style model proposed by Judge & Piccolo (2004). In fact, tools that delivered more flexible, health centred and empathetic justifications, such as ChatGPT, Gemini, Microsoft Copilot and Grok (by order), align more with a transformational orientation algorithm. Accordingly, these systems use conditional phrasing, referencing emotional and, in some cases, environmental dynamics (e.g.: workplace, commuting strain), and encourage dialogue solutions, mimicking behaviours consistent with transformational leadership: intellectual stimulation and individualized consideration (Judge & Piccolo, 2004). On the contrary, tools such ChatBOX, which display more structured and rule-based decisions, reflect a more transactional algorithm style. This is reflected by their outputs prioritizing operational clarity, reinforcing standards, and making decisions based on permitted structures, such as remote work allowance or AI acceptance use, which mimics the transactional leadership style, more focused on maintaining normal operations, ensuring tasks are completed through clear expectations and reinforcement (Judge & Piccolo, 2004).

Logically, the way these tools interpret and respond to the different scenarios influences the attitudes HR managers will have upon them. Following Cecil et al. (2024) framework, two different approaches by managers towards the different AI tools emerge: either they reject the algorithm and refuse to use it during their daily tasks, which is known as algorithm aversion, or they adhere to AI-driven advice, known as algorithmic appreciation. These attitudes towards

AI, are culturally and contextually dependent (Tandon et al., 2024), but also rely on the way each AI tool presents its reasoning. Considering this, when presented with a stimulus (the presenteeism scenario), each AI tool answers according to its programming. The outputs may reflect a more transactional behaviour, by showing more rigid, and concise answers (in this case, ChatBOX), or reflect a more adaptative and transformational behaviour (Microsoft Copilot or Grok), which will affect how the HR managers perceive it and act upon them. As transformational algorithms present more fluent, adaptative and thus “human-like” responses, it is more likely that HR managers will appreciate these insights and most likely incorporate them in their final decisions. On the other side, transactional algorithms that reflect rigidity, lack of adaptability or minimal elaboration on their reasoning behind, will more likely provoke attitudes of aversion towards them and thus develop coping mechanisms (Tandon et al., 2024) among HR managers. Having this in mind, the AI tools that would most likely have higher success rates in HR real life applications would be Gemini, Microsoft Copilot or Grok, under these circumstances. The contextual awareness, layered logic and emotional and empathetic language would most likely convince and influence HR managers to rely on their advice.

Among HR managers, justifications are largely grounded in the organization’s work policies. Under scenario one, for instance, where remote work is not allowed and neither are AI tools, participants tend to argue that the employee should go to work *“If there are no remote working options, Noah must go to the office”* [P11]. Under the same scenario, P29 even states, *“If they're not allowed and the company doesn't agree to be flexible, you have no choice but to go”*, taking more consideration for the organization’s policy, rather than the employee’s condition. Furthermore, even when AI tools are accepted, in cases under which remote work is not, the decisions largely remain untouched, encouraging to request a sick leave *“In this case, the company must make an exception justified by a medical sick leave. The conditions for remote working are met, as the employee has access to AI tools that help him with his/her work”* [P87] or go to the office *“If the company doesn't have a teleworking regime, Noah has no option”* [P74], both under the eighth scenario. The same occurs even when the health condition is chronic *“Since the health condition is prolonged, the fact that the employee remains at home could lead to reprisals. The employee must therefore go to the office or request sick leave to justify their absence”* [P101] (see Annex E, Scenario 7). When remote work is allowed, the consensus is based around the decision that the employee should remain at home and recover, as the conditions to work outside the office are met *“If you have this flexibility, then it's best to stay at home until you're well again”* [P40] under scenario two, *“If the company has a culture that supports remote working and has the tools to help Noah do his job, there's no reason for*

Noah to go to the office and suffer unnecessarily” [P47] under scenario four, and “Noah doesn't need to go to the office often to carry out his work” [P87] under scenario five. Interestingly, when remote work was allowed and the health condition was temporary, participants responses varied widely, missing a consensus if the employee should, or not go to work while ill. Under the second scenario, P71 stated, “Noah must act on how he feels and is unlikely to go, as his health problem causes disruption during the working day and could have implications for how he can return home” and P74 stated, “If the possibility exists, we must ensure the employee's well-being. With the option of teleworking, the employee is more comfortable and fulfils their workload”, while P75 commented, “As the health condition is temporary, the employee must present himself in person at the office”, following the same line of thought as P66, “As it's a temporary problem, I think it's important to spend a few days in the office to foster a collaborative spirit” (See Annex E, Scenario 2).

Lastly, making the joint with the Dual-Process model proposed as framework, the comparison between generative intelligence tools and HR managers in presenteeism scenarios can be interpreted as a contrast between agents dominated by System 2 logic and those capable of integrating both systems. AI tools, by design, simulate rational processing: their outputs are structured, rule-based and analytically coherent, reflecting mostly the principles of the rational system (System 2). With that said, they lack experiential memory and affective processing, and while some advanced models may simulate empathy through language generations (such as Microsoft Copilot or Grok), their reasoning remains fundamentally detached from emotional intuition. On the other hand, HR managers operate within a hybrid cognitive framework, as their decisions may be shaped by intuitive impressions, and emotional resonance, while also engaging in formal analysis and policy interpretation, which reflects the merge of System 1 and 2 together. This duality allows for more flexible, context sensitive judgements that may vary across scenario (reflected by the higher variances on responses), reflecting the dynamic interplay between experientiality and rationality (according to Epstein (1994) initial definition).

6. DISCUSSION

The present research aimed to delve deeper into how generative intelligence tools and HR managers interpret presenteeism scenarios, by answering three questions: whether HR managers and generative intelligence tools vary consistently in their evaluations across scenarios, whether both HR and AI tools are able to differentiate between different types of scenarios, and whether there are significant differences between the evaluations of human and AI agents. The findings show that both HR and AI tools showed sensitivity to scenario variations. However, only some AI tools produced evaluations comparable to those of HR managers, by showing rating patterns that were somewhat similar to human decision-making. In contrast, Grok notably diverged, with different ratings and more variability in the decision making, which indicates lower consistency under the same circumstances. These differences observed call for the attention to the fact that AI systems, though often grouped under a common label and expected to perform in equal ways, do not always operate in uniformity. Different models may apply divergent inferential logics and generate outputs differently.

The present study provides empirical insights into the commonalities and differences between human and AI decision-making. It responds directly to an emerging challenge in HR management and lays upon the integration of AI in decision-making, without compromising or substituting human judgment. By comparing structured evaluations across raters, the study reveals which tools most accurately simulate human reasoning, and which diverge from it. These findings reflect a benchmark for future research on AI-assisted HR practices, and help organizations critically assess with platforms suit best, when employee well-being is the core centre. Furthermore, it provides a methodology that blends situational judgment testing with AI behaviour analysis, which proposes a model for further evaluation studies, highlighting the risks of inconsistency but also the potential for AI use in organizational contexts that demand precision, sensitivity, and empathy.

6.1. Theoretical contributions

The present research contributes significantly to theoretical literature, by exploring and making clear various dimensions of generative intelligence tools in decision-making, specially under ambiguous and highly subjective subjects such as presenteeism. It contributes to presenteeism literature by reframing it not only as a behavioural act, such a going to work while ill (Hemp,

2004; Karanika-Murray & Cooper, 2018) but also as a multidimensional decision shaped by individual perception and organizational flexibility.

According to the Dual-Process Theory, thought is divided between two systems. While the experiential system (System 1), operates automatically and effortlessly resulting in holistic and context specific responses shaped by accumulated experience, the rational system (System 2), becomes often characterized by intentional and effortful processing, reflecting analytically coherent and context-independent responses (Epstein, 1994; Kahneman, 2003). The present study contributes to solidify the understanding of how AI can mimic human cognitive architecture by interpreting the differences observed in the responses. By applying this framework as a baseline for the findings, the comparison between generative intelligence tool and HR managers in presenteeism scenarios becomes enriched as it opens light into the contrast between agents predominantly dominated by the rational system (System 2) and those capable of integrating both experience and rationality into the decision-making process. The tendency for AI tools to produce consistent responses aligns with the characteristics of System 2, whereas the variability and emotional nuance in human evaluations suggest the influence of System 1. Nonetheless, the ability of HR managers to adapt their reasoning accordingly reflects the integrative function of the dual systems, where intuitive responses where HR managers may base their decisions on experience (by past occurrences and knowledge of the consequences) while balancing them with rationality (deciding on what is best on a certain scenario, having in mind the conditions). By situating the comparison with the Dual-Process model, the present investigation gains a deeper conceptual grounding, as it makes possible to interpret not only what decisions are made, but how they are cognitively constructed and justified. This perspective also highlights the limitations of purely rational systems under more subjective and complex domains, where emotional and contextual sensitivity play a critical role. With that said, by doing so, the study contributes to ongoing discussions about the nature of judgment, the boundaries of artificial reasoning, and the potential for more human-aligned decision processes in organizational settings.

Furthermore, the present study expands previous literature by including the relational and communicative dynamics reflected by generative intelligence tools when placed in managerial roles, which is enabled by analysing the findings through Judge and Piccolo (2004) perspective on different leadership styles. Drawing on the Transformational versus Transactional Leadership Theory (Judge & Piccolo, 2004), the study introduces an enhanced framework for classifying AI-generated responses according to their implicit leadership style. While tools that produce structured, rule-based and compliance-oriented outputs are perceived as reflections of

a more transactional leadership style and thus, less likely to provoke algorithmic aversion (Cecil et al., 2024) on those who seek for their contribution, some tools are able to incorporate empathetic phrasing, conditional reasoning and greater contextual sensitivity, being perceived as transformational “leaders” in nature and thus, enhancing the algorithmic appreciation effect on users. This understanding that different generative-intelligence tools produce different outputs with different communication and decision styles, enables a deeper understanding of how AI tools may simulate human-like leadership behaviours and how these behaviours influence the perceived legitimacy and emotional resonance of their decisions.

The study follows Hemp’s (2004) and Johns’ (2010) arguments that presenteeism decisions are not dictated solely by symptom severity but by how the condition is perceived, and the environment around. In fact, both human and AI raters modified their recommendations based not just on whether the illness was chronic or temporary, but on contextual factors such as remote work availability and organizational attitudes towards the use and acceptance of AI. This demonstrates that judgment is shaped by policy frameworks, perceived legitimacy of support tools and cultural norms, rather than medical conditions alone. Moreover, findings support Aronsson & Dallner’s (2005) and Freches’ (2017) work: when remote work or AI usage was discouraged by the organization, scenario ratings tended toward attendance despite the presence of significant health constraints.

The study also reinforces the argument that remote work flexibility acts as a protective factor against presenteeism (Aronsson & Dallner, 2005; Bailey & Kurland, 2002; Demerouti et al., 2001). HR managers and AI platforms alike were more likely to recommend staying at home when remote work was permitted, following Bailey & Kurland (2002), Demerouti et al. (2001), and Kinman (2019), who emphasize the role of adaptative work structures in preserving employee well-being. This also aligns with Bierla et al. (2013), who suggests that rigid work arrangements pressure attendance, an idea proved by the clear shift in decision logic observed across scenarios where flexibility was absent.

Furthermore, the findings contribute to discussions around the role and limitations of generative intelligence in HR decision-making. Previous literature has questioned whether AI can meaningfully interpret ethical and emotional nuance (D’Cruz et al., 2022). In fact, while previous literature results affirm that AI lacks human empathy in the true sense (Booch et al., 2001; D’Cruz et al., 2022), the present results make this analysis more complex. Generative intelligence tools, such as Grok, simulated emotionally aware language, referencing stress, organizational culture and employee doubts, suggesting not empathy, but output structures that are able to influence how advice is perceived and make it more “human-like”. This complexity

expands Booch et al.'s (2001) argument that mimicry of ethical framing may be sufficient for generating trust in certain decision environments. However, not all tools showed the same sensitivity as ChatBOX, for instance showed rule-based logic and stricter outputs, revealing that generative AI is not a homogeneous category.

Additionally, by comparing generative intelligence tools to human decision-makers across standardized scenarios, the study supports Raisch and Krakowski's (2021) proposition that organizations benefit most when AI complements, not replaces, human judgement. Accordingly, HR managers showed a broader range of responses and justified their decisions with references to fairness, responsibility and individual sensitivity. AI tools, in contrast, produced consistently patterned recommendations within their programs. This difference highlights the unique value of human discretion in more subjective contexts. For instance, Grok's variability across scenarios also showed that not all generative intelligence tools maintain internal consistency, suggesting risks when algorithms are used without sufficient control or oversight.

This study advances that presenteeism judgments, both made by humans or generative intelligence tools, are deeply influenced by organizational context, perceived legitimacy and ethical framing. While some AI platforms mimic human reasoning with high accuracy, others reveal procedural rigidity or inconsistent outputs. These findings underscore that AI is not uniform and should be positioned as a complement to, not a replacement for human decision-making.

6.2. Practical implications

The results of this study offer clear and targeted guidance for organizations and developers regarding presenteeism decision-making. In fact, one of the most significant findings is that remote work availability (Kinman, 2019) is the strongest determinant of whether employees are advised to stay at home or go to work. Across all eight scenarios, both HR managers and AI platforms were significantly more likely to recommend staying at home when remote work was allowed. Scenarios that differed only by remote work policy yielded statistically significant mean differences in ratings, regardless of health condition or AI acceptance. This suggests that for organizations seeking to reduce presenteeism, flexible remote work policies should be defined and accessible (McNall et al., 2010), as they influence decision even more than the severity of the health condition.

Moreover, the results revealed that HR managers overall interpreted scenarios through the lens of organizational constraints, particularly the absence or allowance of remote work.

Accordingly, qualitative responses showed that health was often secondary to what was organizationally permitted. This has practical consequences as, when remote work is not allowed or not available, decisions tend toward encouraging attendance, even under chronic conditions. Having this in mind, the findings suggest that organizations must encourage health and well-being in the first place (Jonhs, 2010), avoiding placing decision pressure on employees to prioritize the organization's final interests.

Furthermore, the present study found that generative intelligence tools vary in judgement style and consistency. While ChatGPT and Gemini closely aligned with HR managers, Microsoft Copilot and Grok diverged. While Copilot showed highly consistent but stricter decisions, Grok delivered expressive and human-like reasoning but with high internal variability. This reflects that organizations must evaluate each AI tool before adoption, as their interpretive behavior may affect decisions and overall outcomes. Accordingly, adoption should be aligned with organizational decision style, ethical tone and communication preferences.

Finally, findings on AI tools behavior showed low or null variance, especially for tools like Microsoft Copilot, which suggests rigid reasoning. Contrarily, HR managers demonstrated greater rating variability, which shows the importance of human discretion in ambiguous cases. While AI may contribute with consistency, human judgment provides contextual depth, especially when policies are unclear, or employee well-being is in question. Considering this, AI should be implemented as a supporting system, rather than a replacement for HR decision-making in presenteeism context.

6.3. Limitations and Suggestions for further research

Despite the efforts to enhance the rigor of the study, some limitations are acknowledged.

Although scenario-based methods are a practical tool in health decision research (Corstjens et al., 2017; Lievens & Patterson, 2011; Patterson et al., 2016), they are simplified real-life situations. Having this in mind, HR managers may response differently in real-life situations, where emotional and interpersonal dynamics play a bigger role. For instance, the decision to use a neutral name for the employee was intended to avoid gender-related biases in scenario interpretation. However, by omitting the gender, the effect of this dimension on decisions (that may happen subconsciously in real scenarios) was not explored. Additionally, the sample of HR managers was not large enough to represent the full diversity of the field, broader studies with more participants from different cultural background or leadership styles would allow for richer comparisons and greater confidence in the results.

Furthermore, although this study was conducted using free versions of the selected generative intelligence tools, the results are still considered representative of their core decision-making behaviour. In fact, the responses reflected consistent logical structures, contextual reasoning across scenarios, attributes that are foundational to the model architecture and not exclusively dependent on premium versions. In light of this, although premium versions may offer expanded capabilities such as longer responses, faster generation or enhanced contextual memory, these features are unlikely to significantly impact the decision outcomes in structured scenarios presented in the study. Accordingly, the scenarios were well-defined and presented limited input complexity, which helps to reduce the likelihood that paid-version additional features would impact the final recommendations. Furthermore, qualitative analysis of justifications is linked to subjectivity meaning the interpretation is still shaped by the researcher's context and background knowledge although the efforts to maintain the rigor of the analysis. Despite the efforts made to maintain rigor, interpretation is still shaped by the researcher's context and background knowledge.

Nonetheless, these limitations are perceived as providing avenues for future research. One would be to analyse the algorithmic appreciation or algorithmic aversion (Cecil et al., 2024) effect of AI tools on HR managers, under subjective matters, and what preferences do HR highlight. By analysing which tools HR managers rate as more persuasive, helpful or trustworthy, and why, researchers would be able to uncover deeper insights into AI perceive legitimacy. Furthermore, re-running the present study at a later point may offer meaningful longitudinal insights. AI tools go through programming updates which might change the way they respond and rate scenarios and new generative tools appeared along the data collection period (e.g.: Deep Seek), which would be an interesting addition to the present investigation.

Another important emphasis for future research would be the introduction of more complex scenarios with other contextual variables used in presenteeism literature, such as pay, permanency of employment or ease of replacement, which are proven to influence presenteeism behaviours (Johns, 2010). Furthermore, creating a link with other attendance behaviours, secured by previous literature, such as the intention to leave, would help solidify and provide a continuum for the findings of this study.

Concluding, this study becomes a valuable opportunity for future studies to further validate and extend the present findings by capturing a more comprehensive picture of the dimensions that influence presenteeism decision-making and the differences between the different AI tools (and some that might be born after this study) which would help immensely organizations going through digital transformation.

7. CONCLUSION

The growing integration of generative artificial intelligence tools inside the business landscape is profoundly transforming how organizations maintain their daily operations (Okatta et al., 2024). While AI is already used for recruitment, performance, and talent analytics (Jia et al., 2023), its role under sensitive judgments, such as presenteeism, requires deeper understanding.

This study examined how generative intelligence tools evaluate various presenteeism scenarios, drawing on the Dual-Process Theory and leadership frameworks to interpret their decision-making processes, reinforcing the need to examine how these tools behave, reason, and communicate (Booch et al., 2021; D'Cruz et al., 2022), so their use in decision-making aligns with human reasoning and the nuanced realities of workplace well-being. Through a situational judgement test administered to both human and non-human agents, the study examined temporal variation, scenario differentiation, and overall disparities in presenteeism scenario evaluations between human and non-human agents. The findings revealed that while all tools consistently prioritized employee health and well-being, the way they communicate varies significantly. Tools such as Grok, Gemini or Microsoft Copilot demonstrated a transformational orientation, offering empathetic and context-aware responses, while others, such as ChatBOX reflect a more transactional logic, more stringently aligned with their programming. Furthermore, while AI tools reflect a more rational cognitive process, they are still not able to intertwine both experiential and rational cognitive reasoning characteristic of human cognition. This diverse approach highlights that different tools behave differently, as they embedded in their logic and programming rules, which directly influence how decisions are taken and communicated.

By revealing these asymmetries, the study contributes to the growing body of literature on artificial intelligence in organizational decision-making (Budhwar et al., 2023; Jia et al., 2023; Okatta et al., 2024), offering empirical evidence of the limitations and strengths of algorithmic judgment in HR contexts. It suggests that generative intelligence tools, for now, should not be seen as substitutes for human decision-making, but rather as collaborative partners whose consistency, and contextual awareness can enhance human judgment when thoughtfully integrated. As organizations increasingly rely on these tools, it becomes essential to ensure that their deployment is guided by transparency and accountability, while understanding its embedded rules within each tool. The present research stands as a testament to the enduring necessity of human perspective in navigating the layered realities of organizational life.

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ANNEXES

Annex A – Descriptive statistics

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	95	73.1	79.8	79.8
	Male	24	18.5	20.2	100.0
	Total	119	91.5	100.0	
	System	11	8.5		
Missing		130	100.0		
Total					

Tenure

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 year	22	16.9	18.5	18.5
	1 to 3 years	49	37.7	41.2	59.7
	4 to 6 years	24	18.5	20.2	79.8
	7 to 10 years	11	8.5	9.2	89.1
	More than 10 years	13	10.0	10.9	100.0
	Total	119	91.5	100.0	
Missing	System	11	8.5		
Total		130	100.0		

Market Sector

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Industrial	4	3.1	3.4	3.4
	Commerce	10	7.7	8.4	11.8
	Services	47	36.2	39.5	51.3
	Technology	31	23.8	26.1	77.3
	Health	3	2.3	2.5	79.8
	Education	1	.8	.8	80.7
	Other	23	17.7	19.3	100.0
	Total	119	91.5	100.0	
Missing		11	8.5		
Total		130	100.0		

Annex B – Presenteeism Scenarios

Scenario	Conditions
1. Noah has a chronic health problem that causes him constant back pain and requires regular care management. In his organisation, remote working and the use of Artificial Intelligence-based tools (which could help Noah perform his tasks) are not allowed.	chronic health condition, AI use not accepted , remote work not allowed
2. Noah has had a temporary allergic problem for the last few days, which has caused him some constraints at work. Although his organisation does not take kindly to the use of Artificial Intelligence-based tools, it supports flexibility, thus enabling remote working.	temporary health condition, AI use not accepted , remote work allowed
3. Noah has a chronic health problem, which causes him constant back pain and requires regular care management. Your organisation supports the use of Artificial Intelligence-based tools to facilitate tasks, while allowing your employees to work from home.	chronic health condition, AI use accepted , remote work allowed
4. In recent days, Noah has had a temporary allergic problem, which has caused him some constraints at work. Your organisation not only allows the use of Artificial Intelligence-based tools to perform tasks, but also offers its employees the option of working remotely.	temporary health condition, AI use accepted , remote work allowed
5. Noah has a chronic health problem that causes him constant back pain and requires regular care management. Although his organisation doesn't take kindly to the use of Artificial Intelligence-based tools, it supports flexibility, thus enabling remote working.	chronic health condition, AI use not accepted , remote work allowed
6. In recent days, Noah has had a temporary allergic problem, which has caused him some constraints at work. Not only does his organisation not allow the use of Artificial Intelligence-based tools, it also imposes a totally face-to-face work regime.	temporary health condition, AI use not accepted , remote work not allowed
7. Noah has a chronic health problem, which causes him constant back pain and requires regular care management. The organisation strongly encourages the use of Artificial Intelligence tools to manage the productivity and performance of its employees. However, employees can't work from home, so they have to travel to the facilities every day.	chronic health condition, AI use accepted , remote work not allowed
8. Noah has had a temporary allergic problem over the last few days, which has caused him some constraints at work. His organisation supports the use of Artificial Intelligence tools to perform tasks. However, the organisation supports a fully face-to-face working system, which means that employees have to go to the office every day.	temporary health condition, AI use accepted , remote work not allowed

Annex C – Mean ratings by respondent

		HR Manager		Gen AI Tool	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Scenario	1	3.23	1.539	2.33	1.093
	2	2.03	1.030	2.27	1.081
	3	1.80	1.064	1.93	1.202
	4	1.89	.986	2.17	1.147
	5	2.29	1.071	2.40	.894
	6	3.42	1.722	3.07	1.230
	7	3.23	1.579	2.87	.973
	8	3.38	1.674	3.23	1.382

Annex D – Interaction and Relationships between variables

Interaction between scenario ratings and respondents

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Scenario	Pillai's Trace	.277	4.537 ^b	7.000	83.000	<.001	.277
	Wilks' Lambda	.723	4.537 ^b	7.000	83.000	<.001	.277
	Hotelling's Trace	.383	4.537 ^b	7.000	83.000	<.001	.277
	Roy's Largest Root	.383	4.537 ^b	7.000	83.000	<.001	.277
Scenario * Rater Type	Pillai's Trace	.691	1.992	35.000	435.000	<.001	.138
	Wilks' Lambda	.450	2.099	35.000	351.579	<.001	.148
	Hotelling's Trace	.933	2.170	35.000	407.000	<.001	.157
	Roy's Largest Root	.435	5.402 ^c	7.000	87.000	<.001	.303

a. Design: Intercept + Rater_Type

Within Subjects Design: Scenario

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Analysis of the relationship between scenarios

Scenario	Scenario	Mean Difference	Std. Error	Sig. ^b	95% Confidence Interval for Difference ^b	
					Lower Bound	Upper Bound
1	2	.256	.248	.306	-.237	.749
	3	.572*	.237	.018	.100	1.044
	4	.362	.250	.152	-.135	.859
	5	.101	.214	.638	-.323	.525
	6	-.642*	.233	.007	-1.105	-.179
	7	-.444*	.179	.015	-.800	-.089
	8	-.776*	.224	<.001	-1.221	-.330
2	3	.316	.198	.114	-.078	.710
	4	.106	.159	.506	-.210	.423
	5	-.155	.209	.462	-.571	.261
	6	-.897*	.232	<.001	-1.358	-.437
	7	-.700*	.258	.008	-1.213	-.187
	8	-1.031*	.265	<.001	-1.558	-.504
3	4	-.210	.157	.185	-.522	.103
	5	-.471*	.191	.016	-.851	-.091
	6	-1.214*	.238	<.001	-1.686	-.741
	7	-1.016*	.237	<.001	-1.487	-.545
	8	-1.347*	.256	<.001	-1.856	-.839
4	5	-.261	.210	.217	-.679	.157
	6	-1.004*	.214	<.001	-1.428	-.579
	7	-.806*	.242	.001	-1.287	-.326
	8	-1.138*	.261	<.001	-1.656	-.620
5	6	-.743*	.240	.003	-1.219	-.267
	7	-.545*	.204	.009	-.950	-.140
	8	-.876*	.228	<.001	-1.329	-.424
6	7	.197	.203	.334	-.207	.602
	8	-.134	.189	.482	-.510	.243
7	8	-.331*	.136	.017	-.602	-.060

Based on estimated marginal means

The mean difference is significant at the .05 level.*

Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments)_b

Analysis of the relationship between raters

Scenario	Rater	Rater	Mean Difference	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
1	HR	ChatBOX	1.06	.591	1.000	-.72	2.85
		ChatGPT	.40	.591	1.000	-1.39	2.18
		Gemini	.40	.591	1.000	-1.39	2.18
		Microsoft Copilot	2.23*	.591	.004	.45	4.01
		Grok	.40	.591	1.000	-1.39	2.18
2	HR	ChatBOX	.70	.414	1.000	-.55	1.95
		ChatGPT	.03	.414	1.000	-1.22	1.28
		Gemini	.36	.414	1.000	-.89	1.61
		Microsoft Copilot	-.97	.414	.324	-2.22	.28
		Grok	-1.30*	.414	.034	-2.55	-.05
3	HR	ChatBOX	.63	.443	1.000	-.70	1.97
		ChatGPT	-.37	.443	1.000	-1.70	.97
		Gemini	.13	.443	1.000	-1.20	1.47
		Microsoft Copilot	.47	.443	1.000	-.87	1.80
		Grok	-1.53*	.443	.013	-2.87	-.20
4	HR	ChatBOX	.89	.406	.456	-.33	2.12
		ChatGPT	-.11	.406	1.000	-1.33	1.12
		Gemini	.23	.406	1.000	-1.00	1.45
		Microsoft Copilot	-1.11	.406	.114	-2.33	.12
		Grok	-1.27*	.406	.034	-2.50	-.05
5	HR	ChatBOX	.29	.435	1.000	-1.02	1.60
		ChatGPT	-.21	.435	1.000	-1.52	1.10
		Gemini	-.21	.435	1.000	-1.52	1.10
		Microsoft Copilot	.29	.435	1.000	-1.02	1.60
		Grok	-.71	.435	1.000	-2.02	.60
6	HR	ChatBOX	1.42	.631	.409	-.49	3.32
		ChatGPT	-1.25	.631	.755	-3.15	.65
		Gemini	.42	.631	1.000	-1.49	2.32
		Microsoft Copilot	-.58	.631	1.000	-2.49	1.32
		Grok	1.75	.631	.102	-.15	3.65
7	HR	ChatBOX	.90	.594	1.000	-.89	2.69
		ChatGPT	-.77	.594	1.000	-2.56	1.02
		Gemini	.06	.594	1.000	-1.73	1.86
		Microsoft Copilot	1.23	.594	.618	-.56	3.02
		Grok	.40	.594	1.000	-1.39	2.19
8	HR	ChatBOX	1.22	.663	1.000	-.78	3.22
		ChatGPT	-1.28	.663	.845	-3.28	.72
		Gemini	.05	.663	1.000	-1.95	2.05
		Microsoft Copilot	.38	.663	1.000	-1.62	2.38
		Grok	.38	.663	1.000	-1.62	2.38

Based on observed means.

The error term is Mean Square(Error) = 2.414.

* The mean difference is significant at the .05 level.

Annex E – Qualitative analysis

Evidence quotes – Scenario 1

Scenario	Quote [respondent]
1 - Chronic health condition, AI use not accepted, remote work not allowed	<p>Given your chronic health condition that requires regular management and the lack of support for AI-based tools in your organization, it may be better to prioritize your health over attending the office [ChatBOX]</p> <p>If your health condition could worsen or become harder to manage by being in the office, you should prioritize your well-being. On the other hand, if your condition is manageable today and attending aligns with your work responsibilities, going could be considered. Prioritize your health and only attend if it won't compromise your condition. [ChatGPT]</p> <p>Given the lack of remote options and the organizational climate, prioritizing your health might be the best course of action. This is a general recommendation. The best decision will depend on your specific circumstances. If possible, try to have an open and honest conversation with your manager about your health concerns and see if there's any flexibility or support available. [Gemini]</p> <p>Given the context you've shared, it sounds like your chronic health condition requires consistent care, and with no remote work options available, going to the office could pose a challenge. Your health and well-being should always come first. If your condition needs regular management and being in the office might compromise that, it's better to prioritize your health. It's essential to communicate with your organization about your needs and find a solution that supports your well-being. [Microsoft Copilot]</p> <p>Considering your chronic health condition requires regular management, I'm concerned about the potential impact of commuting to the office on your well-being. Given the organization's lack of support for AI-based tools and the skepticism among employees, I think it's likely that you'll face additional stress and challenges in the office environment. It might be better to prioritize your health and well-being by taking care of your chronic condition from home, where you can manage your health more effectively and avoid the added stress of commuting and working in an environment that may not be conducive to your needs. [Grokl]</p> <p>If there are no remote working options, Noah must go to the office [P11]</p> <p>If they're not allowed and the company doesn't agree to be flexible, you have no choice but to go. [P29]</p>

Evidence quotes – Scenario 2

Scenario	Quote [respondent]
2 - Temporary health condition, AI use not accepted, remote work allowed	Since remote work is permitted and you have a temporary health condition that can be managed from home, it would be wise to take advantage of the remote work option to focus on your recovery. [ChatBOX]
	Given that your condition can be managed remotely, and remote work is allowed, staying home is the better choice for recovery and productivity. Take advantage of remote work to recover effectively while meeting your work commitments. [ChatGPT]
	Given that remote work is permitted and your condition can likely be managed effectively from home, working remotely today seems like the most reasonable option. This allows you to focus on recovery while minimizing potential disruptions to your colleagues. Important Considerations: Communicate, Inform your manager about your condition and your intention to work remotely. Productivity: Ensure you have a dedicated workspace and a reliable internet connection to maintain productivity. Collaboration, Schedule regular check-ins with your team to stay connected and address any potential communication gaps. [Gemini]
	Since your organization allows remote work, it would be wise to take advantage of that option while you recover. This way, you can manage your health condition effectively without the added stress of commuting and being in the office. Prioritizing your recovery is important, and remote work provides a suitable solution for now. [Microsoft Copilot]
	With remote work permitted, it seems like a perfect opportunity to manage your temporary health condition while recovering. Given the organization's acceptance of remote work, I think it's a great chance to take care of yourself and prioritize your health without having to worry about commuting or navigating an office environment that may not be conducive to your needs. Considering your temporary health condition, I would recommend taking advantage of the remote work option to recover and manage your health. This will likely help you recover faster and more effectively, and you can always discuss your situation with your employer to ensure a smooth transition back to the office when you're feeling better. [Grok]
	As it's a temporary problem, I think it's important to spend a few days in the office to foster a collaborative spirit. [P66]
Noah must act on how he feels and is unlikely to go, as his health problem causes disruption during the working day and could have implications for how he can return home. [P71]	
If the possibility exists, we must ensure the employee's well-being. With the option of teleworking, the employee is more comfortable and fulfils their workload. [P74]	
As the health condition is temporary, the employee must present himself in person at the office. [P75]	
If you have this flexibility, then it's best to stay at home until you're well again. If there are issues that need to be resolved, then you should go to the office. [P40]	

Evidence quotes – Scenario 3

Scenario	Quote [respondent]
3 - Chronic health condition, AI use accepted, remote work allowed	<p>Given that your organization supports AI-driven health tools and allows for remote work, and considering that your chronic health condition would benefit from flexibility, it would be best for you to work from home today to prioritize your health and well-being. [ChatBOX]</p> <p>If working remotely enhances your ability to manage your health condition, it makes sense to take advantage of this option. However, if attending the office adds value to your work or well-being without negatively impacting your health, you could consider going. Prioritize flexibility and health management through remote work, unless there's a compelling reason to attend the office. [ChatGPT]</p> <p>Given the supportive work environment and the potential benefits for your health, working remotely today seems like an excellent choice. This allows you to manage your condition effectively while maintaining your productivity. Important Considerations: Communicate: Inform your manager about your decision to work remotely and discuss any specific accommodations you may need. Utilize Resources: Explore the AI-driven health tools available within your organization and leverage them to support your health management. Prioritize Self-Care: Use the flexibility of remote work to prioritize self-care activities that help you manage your condition. [Gemini]</p> <p>Since your organization allows remote work, it would be wise to take advantage of that option while you recover. This way, you can manage your health condition effectively without the added stress of commuting and being in the office. Prioritizing your recovery is important, and remote work provides a suitable solution for now. [Microsoft Copilot]</p> <p>Given your chronic health condition and the flexibility to work from home, I think it's a great opportunity to prioritize your health and avoid commuting today. Commuting can be stressful and tiring, which may exacerbate your chronic health condition. By working from home, you can avoid the commute and manage your condition more effectively. [Grok]</p> <p>As he has a chronic illness, Noah should only go if he feels he has to go to the office because of a greater need. [HR6]</p>

Evidence quotes – Scenario 4

Scenario	Quote [respondent]
4 - Temporary health condition, AI use accepted, remote work allowed	<p>Since your organization accepts remote work and AI tools, and you have a temporary health condition, it would be advisable to work from home to prioritize your health and comfort during your recovery. [ChatBOX]</p> <p>With remote work available and a temporary health condition, it's advisable to work from home today to prioritize your recovery without compromising productivity. Leverage remote work to focus on your health while fulfilling work responsibilities. [ChatGPT]</p> <p>Given the supportive work environment and the potential benefits for your health, working remotely today is strongly recommended. Important Considerations: Communicate: Inform your manager about your condition and your intention to work remotely. Utilize Resources: Leverage AI tools to streamline your work and improve efficiency. Prioritize Self-Care: Use the flexibility of remote work to prioritize rest and recovery. [Gemini]</p> <p>Leveraging remote work in this situation can help you manage your health while maintaining your productivity. Prioritizing your recovery is important, and working from home will allow you to take care of yourself better. [Microsoft Copilot]</p> <p>Considering your organization's acceptance of remote work and AI tools, and your temporary health condition, I think it's a great opportunity to prioritize your health and work from home today. With remote work options available, you can manage your temporary health condition more effectively and avoid the added stress of commuting and working in an office environment. [Grok]</p> <p>If the company has a culture that supports remote working and has the tools to help Noah do his job, there's no reason for Noah to go to the office and suffer unnecessarily. [P47]</p>

Evidence quotes – Scenario 5

Scenario	Quote [respondent]
5 - Chronic health condition, AI use not accepted, remote work allowed	<p>Given that your chronic health condition could benefit from the flexibility of working from home, and considering the low AI acceptance climate—which might limit your access to advanced health management tools—it's still better to prioritize your health by working from home. You can focus on your well-being even if it means missing out on some resources. [ChatBOX]</p> <p>Given the availability of remote work and the potential benefits for managing your condition, working from home would likely be the better choice. While limited AI support may be a drawback, it doesn't outweigh the health advantages of flexibility. Remote work offers a better balance for health and productivity, even in a low AI acceptance environment. [ChatGPT]</p> <p>Given the significant health benefits of remote work, I recommend working from home today. Communicate: Inform your manager about your decision and the potential benefits of remote work for your health. Explore Alternatives: Research alternative ways to access AI-powered health management tools outside of work, such as personal subscriptions or independent apps. Focus on the Benefits: Concentrate on the positive aspects of remote work, such as flexibility and reduced stress, which can significantly contribute to your overall well-being. [Gemini]</p> <p>Even though the organization has a low AI acceptance climate and you might miss out on some advanced health management tools, the ability to work from home still allows you to manage your health condition better. Prioritizing your well-being is important, and remote work provides a valuable option to help you do so. Balancing your health with work is key, and staying home today would likely be the best choice for you. [Microsoft Copilot]</p> <p>Considering the organization's low AI acceptance climate, which may limit your access to advanced health management tools, and your chronic health condition that could benefit from the flexibility of working from home, I think it's a tough decision. However, given the option to work from home, I would recommend taking advantage of the flexibility to manage your chronic health condition more effectively. While you may not have access to advanced AI tools, you can still prioritize your health and well-being by working in a comfortable and stress-free environment. [Grok]</p> <p>Noah doesn't need to go to the office often to carry out his work. He should go in situations where this is necessary due to the lack of capacity of the support tools. In this sense, it would already alleviate and contribute to his well-being. [P87]</p>

Evidence quotes – Scenario 6

Scenario	Quote [respondent]
6 - Temporary health condition, AI use not accepted, remote work not allowed	<p>Given that you have a temporary health condition and there are no remote work options available, commuting to the office might not be the best choice for your health. Even if you're willing to work, it's important to prioritize your well-being, especially if you're not feeling your best. [ChatBOX]</p> <p>If commuting and working in the office won't worsen your temporary condition or impede recovery, attending could be an option. However, if there's any risk to your health, it's worth discussing accommodations with your organization. Go to the office if you're confident your condition is manageable and the environment won't hinder your recovery. If not, explore alternative arrangements, even if remote work isn't standard. [ChatGPT]</p> <p>Given the lack of remote work options and the potential impact of your temporary condition, I recommend strongly considering staying home today. Communicate: If possible, discuss your situation with your manager. Explain your condition and explore whether any alternative arrangements (e.g., flexible start/end times, reduced hours) might be possible. Prioritize Your Health: If your condition significantly impacts your ability to work effectively or poses a risk to your health, prioritize your recovery. Company Policy: Familiarize yourself with your company's policies regarding sick leave or personal time. [Gemini]</p> <p>While managing your temporary health condition might be challenging, your willingness to work shows your commitment. Make sure to take any necessary precautions and communicate your needs to your employer. If you start feeling worse, don't hesitate to prioritize your health and seek appropriate support. How are you feeling about heading in today? [Microsoft Copilot]</p> <p>Considering the limited AI resources and no remote work permitted, I think it's a challenging situation. Given your temporary health condition, I would recommend prioritizing your health and well-being by avoiding the commute to the office today. The added stress and fatigue from commuting may exacerbate your condition, making it harder to manage. [Grok]</p> <p>Noah will have to apply for sick leave until he is fit to return to work. With no permission for remote work and limited tools, there is no other alternative. [P87]</p>

Evidence quotes – Scenario 7

Scenario	Quote [respondent]
7 - Chronic health condition, AI use accepted, remote work not allowed	<p>Given that your organization strongly encourages the use of AI tools for productivity and health management, and considering your chronic health condition that requires ongoing management, it may be important to utilize those AI tools to help manage your health effectively. [ChatBOX]</p> <p>If the office environment supports your health management through AI tools and accommodations, attending could be beneficial. However, if commuting or being in the office poses risks to your condition, prioritize discussing adjustments with your employer. Attend the office if the benefits of AI tools and support outweigh the challenges posed by your health condition. Make sure your health needs are addressed while at work. [ChatGPT]</p> <p>This is a difficult decision. While the availability of AI tools is a positive, the lack of remote work poses a significant challenge for your health. Communicate your concerns about your health and the limitations of the current work arrangements with your manager. Explore On-site Accommodations: Discuss potential on-site accommodations that could help you manage your condition (e.g., quiet workspace, flexible break times). Prioritize Self-Care: If possible, prioritize self-care activities outside of work hours to mitigate the potential impact of the office environment on your health. [Gemini]</p> <p>Despite your organization's strong encouragement of AI tools for productivity and health management, the inability to work from home may pose a challenge in effectively managing your condition. Prioritizing your health is essential. If possible, communicate your needs with your employer to explore alternatives that can support both your well-being and work responsibilities. Do you need any assistance with how to approach this conversation with your employer? [Microsoft Copilot]</p> <p>Considering your organization's strong encouragement of AI tools for productivity and health management, and your chronic health condition that requires ongoing management, I think it's a great opportunity to take advantage of the AI tools and resources available to you. However, given that employees cannot work from home, I would recommend discussing your situation with your employer to explore potential accommodations or alternatives that can help you manage your chronic health condition while still working in the office. I would suggest exploring options such as flexible work arrangements, ergonomic adjustments, or accommodations that can help you manage your health condition while still being productive and utilizing the AI tools available to you. [GroK]</p> <p>Since the health condition is prolonged, the fact that the employee remains at home could lead to reprisals. The employee must therefore go to the office or request sick leave to justify their absence. [P101]</p>

Evidence quotes – Scenario 8

Scenario	Quote [respondent]
8 - Temporary health condition, AI use accepted, remote work not allowed	<i>Since there is significant support for using AI to aid your work and you have a temporary health condition, it may be beneficial to go to the office to take advantage of those resources. However, if your health condition is severe enough to impact your ability to work effectively or comfortably on-site, you should consider your well-being first. If you feel that you can manage your health condition and benefit from the AI resources at the office, then you should go. Otherwise, prioritize your health. [ChatBOX]</i>
	<i>If your temporary health condition is manageable in the office environment and won't negatively impact your recovery, attending is reasonable. Ensure workplace accommodations (like flexible hours or ergonomic support) are in place if needed. Attend the office, leveraging AI tools and available resources, as long as it aligns with your health needs and recovery. [ChatGPT]</i>
	<i>Given the strong AI support available within your organization, going to the office today might be a viable option. Assess Your Condition: Carefully evaluate how your condition is affecting you today. If it significantly impacts your ability to work effectively, it might be best to stay home.</i> <i>Utilize AI Tools: Leverage the available AI tools to maximize your productivity and minimize the impact of your condition on your work.</i> <i>Communicate: If you encounter any challenges while working on-site, communicate them to your manager. [Gemini]</i>
	<i>Even with your temporary health condition, the support from AI tools can help you manage your tasks and health more efficiently while on-site. Ensure you take any necessary precautions to avoid worsening your condition and make use of the available AI resources to ease your workload. If at any point you feel your condition worsening, don't hesitate to reassess and prioritize your health. Have a good day at work! [Microsoft Copilot]</i>
	<i>Considering the significant support for employees to use AI to aid their work, and your temporary health condition that requires you to work on-site, I think it's a good opportunity to take advantage of the AI tools and resources available to you. Given that you need to work on-site, I would recommend going to the office today and utilizing the AI tools to aid your work and manage your temporary health condition. [Grok]</i>
	<i>If the company doesn't have a teleworking regime, Noah has no option. [P74]</i> <i>In this case, the company must make an exception justified by a medical sick leave. The conditions for remote working are met, as the employee has access to AI tools that help him with his/her work. [P87]</i>