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# The Silent Impact of AI: Unveiling Motivational Side Effects in the Digital Workplace

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## ABSTRACT

As artificial intelligence (AI) becomes increasingly integrated into knowledge-intensive work, questions arise about its psychological side effects. While most research emphasizes productivity, this study explores how AI usage may alter work experiences by reducing perceived social presence and cognitive effort - factors that influence motivation and, in turn, performance. Building on the High-Performance Cycle and related cognitive-motivational frameworks, we propose a mediation model and examine technological self-efficacy as a potential moderator. A cross-sectional study was conducted with professionals who regularly use AI tools in their daily tasks. All variables were measured using validated instruments and analyzed through structural equation modeling and bootstrapped mediation testing. Results show that AI usage significantly reduces both perceived social presence and cognitive effort, which positively influence motivation. Motivation emerged as the strongest predictor of performance, with full mediation confirmed. Technological self-efficacy moderated the link between AI usage and motivation, suggesting individual resilience factors play a key role. These findings emphasize that AI adoption is not psychologically neutral. Even when efficiency improves, the motivational cost may be high if systems erode task meaning or relational depth. This study contributes to theory by identifying indirect psychological mechanisms linking AI to performance and highlights practical implications for motivationally aware AI design and training. Future research should further explore cross-cultural differences, long-term effects, and AI-human collaboration dynamics in evolving work environments.

**Keywords:** Artificial intelligence, Motivation, Social presence, Cognitive effort, Performance, Structural equation modeling, Workplace psychology

## INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technologies in organizational environments is transforming the nature of work. What was once deemed exclusively human (e.g., decision making, knowledge processing, creative problem solving) is increasingly supported - or supplanted - by AI systems (Brynjolfsson et al., 2025). While such technologies promise enhanced efficiency and productivity, they also raise critical questions about the human side of work: How does the integration of AI change employees' motivational drivers, perceptions of agency, engagement with tasks, and ultimately performance?

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In particular, the deployment of AI in tasks that were formerly performed by humans may impact key psychological and behavioural elements - for instance, reducing opportunities for cognitive challenge, diminishing social interaction or presence, and altering perceptions of task meaningfulness. For example, recent work suggests that AI use can reduce cognitive effort requirements in tasks, which may sound beneficial, but this very reduction may lead to reduced personal investment or decreased feelings of competence (Chen, 2025). At the same time, studies on human-AI collaboration indicate that lower social presence (i.e., the feeling of interacting with another human or being socially connected) in AI augmented work may undermine trust, engagement and motivation (Zhang et al., 2021). Despite the emerging research, there remains a paucity of studies addressing how these psychological mechanisms mediate the relationship between AI usage and work performance in knowledge intensive tasks.

This paper addresses that gap by investigating how the use of AI in complex tasks affects employees' motivation and performance, using knowledge work (with an example of informatics related tasks) as an illustrative case. Drawing on the High Performance Cycle of Locke and Latham (2002), which emphasises the role of goal setting, effort, persistence and performance, as well as concepts of social presence, cognitive effort, perceptual fluency, and the potential distortions from the Dunning-Kruger effect (Dunning and Kruger, 1999), we propose a process model in which AI utilisation reduces perceived social presence and cognitive effort, thereby decreasing employee motivation and ultimately performance.

To empirically test our model, we carry out a quantitative study with employee respondents engaged in informatics oriented tasks within organisations. We operationalise AI usage as our independent variable, and self reported performance as our dependent variable, with perceived social presence, cognitive effort, and motivation specified as mediators. Data are analysed using structural equation modelling (SEM) to test direct and indirect effects. The aim is to deepen theoretical understanding of human-AI interaction in work settings and to inform practitioners about the conditions under which AI may inadvertently undermine - rather than enhance - employee motivation and performance.

By focusing on informatics related tasks as a representative context (with an outlook that the findings may generalise to other complex task domains), the study contributes both to theory (by integrating motivational, cognitive and social psychological mechanisms in the AI work interface) and practice (by signalling when AI deployment may backfire from a human performance perspective).

## THEORETICAL BACKGROUND

One of the most widely accepted frameworks in work and organizational psychology is the High-Performance Cycle proposed by Locke and Latham (2002), which posits that clearly defined goals, high self-efficacy, and feedback mechanisms jointly promote motivation, effort, and ultimately job performance. Motivation channels attention and energy toward task success, and goal clarity and perceived competence play a central role in sustaining effort. In AI-supported environments, however, these dynamics may shift. When AI takes over cognitively demanding tasks, individuals may experience a reduced sense of agency or control. Automated feedback and diminished self-construction of goals could interfere with the motivational feedback loop described in the High-Performance Cycle (Locke and Latham, 2002).

Social presence, defined as the perceived social or emotional engagement in mediated interaction (Short, Williams, and Christie, 1976), becomes relevant in AI contexts where human collaborators are replaced or reduced. Zhang et al. (2021) found that lower social presence in AI-supported settings reduces trust and engagement, while Oh et al. (2018) showed that social presence correlates positively with satisfaction and motivation. A lack of perceived interaction may reduce accountability and social energy, both of which are important for intrinsic motivation.

Cognitive effort, or the mental resources invested in tasks, is another critical factor. Westbrook et al. (2015) emphasize that effort signals engagement and ownership. When AI automates parts of the task, perceived effort may decrease. Although this can improve efficiency, it can also reduce the psychological value of success. Perceptual fluency - the ease of processing information - can further exacerbate this effect. Reber et al. (2004) note that overly fluent tasks may lead to underinvestment or disengagement. As Evans (2024) argues, cognitive offloading through AI may unintentionally reduce intrinsic motivation when success is no longer perceived as self-driven.

The Dunning-Kruger effect (Dunning and Kruger, 1999) adds a further layer to this discussion. Individuals with limited competence may overestimate their skills, and this tendency may be amplified in AI-supported environments. When users benefit from intelligent systems without understanding them, they may misattribute outcomes to personal ability, distorting feedback and weakening the learning process. In complex tasks, such misperceptions can reduce adaptive growth and long-term performance.

This study integrates these theoretical constructs into a comprehensive path model. The High-Performance Cycle serves as the motivational core, while social presence and cognitive effort represent mediating psychological states. Perceptual fluency and the Dunning-Kruger effect provide further explanatory depth by highlighting changes in perceived effort and self-assessment. Prior research by Jia et al. (2025) and Wu et al. (2025) has examined similar mechanisms. However, this study contributes a novel integration by explicitly modeling how AI use influences performance via cognitive and motivational pathways, while also accounting for distorted perceptions and social-emotional disruptions.

## HYPOTHESES AND CONCEPTUAL MODEL

We propose a path model in which the independent variable (IV) is the degree of AI usage in task processing, and the dependent variable (DV) is employee performance. The relationship between these two variables is mediated by three key constructs: perceived social presence, cognitive effort (or perceptual fluency), and motivation. Specifically, the model assumes that

AI usage reduces perceived social presence and alters the level of cognitive effort required, potentially increasing the perceived fluency of tasks. These altered perceptions are expected to influence motivation, which in turn drives performance outcomes.

Additionally, the model allows for the possibility of moderation. Technological self-efficacy, or an individual's perceived competence in handling AI tools, may differentially affect certain pathways in the model, with the influence of AI usage on motivation appearing especially susceptible. In other words, individuals with higher self-efficacy may be less susceptible to the motivational side effects of AI integration. This conceptual framework captures both the cognitive and emotional dynamics of AI-mediated work, highlighting the importance of subjective experience in determining performance outcomes.

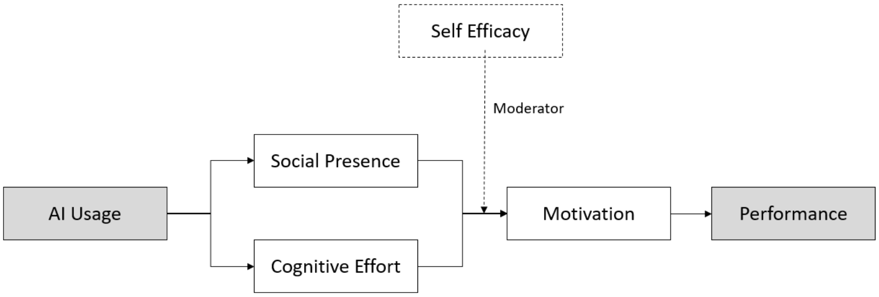


**Figure 1:** Conceptual path model (own illustration).

Below are our formal hypotheses, with theoretical justification and linkage to the model.

*H1a: AI usage is negatively related to perceived social presence.*

When tasks are supported or replaced by AI systems, the human-human interaction (or sense of interacting with another conscious agent) may decline. Research in mediated settings emphasises that reduced social presence harms engagement and commitment (Oh et al., 2018). Studies of AI in collaborative tasks show that automation can undermine social cues.

*H1b: AI usage is negatively related to cognitive effort (or positively related to perceptual fluency).*

AI can reduce the mental workload by taking over complex processing, thereby lowering required cognitive effort. While this seems positive, it may reduce subjective investment and sense of challenge. For instance, research finds that AI collaboration improves immediate performance but results in lower intrinsic motivation.

*H2a: Lower perceived social presence is negatively related to motivation.*

According to motivational theory (e.g., the High Performance Cycle, Locke and Latham, 2002), feelings of meaningful connection, feedback and goal oriented interaction help sustain effort and persistence. If social presence declines, motivation may suffer.

*H2b: Lower cognitive effort or higher perceptual fluency is negatively related to motivation.*

If tasks are perceived as too easy or lacking challenge (high fluency), the motivational drive to invest effort can diminish. Cognitive load literature suggests that too low or too high cognitive demand both reduce motivational engagement.

*H3: Motivation is positively related to performance.*

This is directly drawn from the High Performance Cycle (Locke and Latham, 2002) which posits that effort, persistence and strategy (which stem from motivation) lead to improved performance.

*H4: Perceived social presence and cognitive effort/fluency mediate the relationship between AI usage and motivation.*

AI usage affects the psychological experience (social presence, cognitive effort/fluency), and these in turn influence motivation. This mediation chain is supported by emerging AI–work research showing that AI's effects on motivation are partially indirect. For example, recent work shows AI boosts performance but undermines motivation due to altered task experience.

*H5: Motivation mediates the relationship between perceived social presence / cognitive effort/fluency and performance.*

This is the final step in the path from experience to outcome: altered task experience leads to motivation, and motivation, in turn, leads to performance.

*H6 (Optional moderator hypothesis): Technological self efficacy (or AI competence) moderates the effect of AI usage on motivation, such that the negative effect of AI usage on motivation is weaker for employees with high self efficacy.*

Individuals confident in using technology may interpret AI assistance differently (e.g., as supportive rather than controlling), thus mitigating the negative effect. Although direct literature is scarce, research on human AI collaboration indicates that user characteristics (such as motivation and perceived competence) shape outcomes.

In summary, the model posits that the use of AI in task environments can initiate a chain of psychological consequences - reduced social presence and altered cognitive engagement - which in turn diminish motivation, thereby reducing performance. Individuals' technological self efficacy may buffer these negative pathways.

## METHODOLOGY

To investigate the proposed mediation model, we employed a quantitative, hypothesis-driven approach using structural equation modeling (SEM). A cross-sectional survey was conducted among knowledge workers from various industries who regularly engage in cognitively demanding digital tasks, some of which are supported or augmented by AI technologies (e.g., large language models, automation tools, predictive systems). Using purposive sampling, we targeted individuals with documented experience in using AI tools at work. Participants (N = 297) met inclusion criteria requiring them to be over 18 years of age, currently employed in digital roles, and to have prior exposure to AI systems, as confirmed through a filter item in the survey. This sample size exceeds recommended guidelines for models involving five latent variables (Kline, 2015).

Data collection was performed via an online questionnaire disseminated through LinkedIn groups, professional mailing lists, and curated networks in the technology and consulting sectors. Participation was anonymous and voluntary. All constructs were assessed using validated Likert-scale items (1 = strongly disagree to 7 = strongly agree), adapted to the AI-supported work context. Minor phrasing adjustments ensured relevance to participants' experiences.

Data analysis followed a two-step SEM procedure using AMOS. First, confirmatory factor analysis (CFA) assessed the measurement model, evaluating internal consistency, convergent validity, discriminant validity, and global model fit using CFI, RMSEA, and SRMR. Second, the structural model was tested to estimate the hypothesized relationships, including direct, indirect, and mediated effects. Mediation was examined through bias-corrected bootstrapping with 5,000 resamples. To further assess the model's robustness, a multi-group analysis was conducted to test for moderation effects of technological self-efficacy.

| Construct | Source/Scale | Example Item |
|---|---|---|
| **AI Usage** | Adapted from Venkatesh et al. (2003); Jia et al. (2025) | "I regularly use AI tools to complete my work tasks." |
| **Perceived Social Presence** | Adapted from Short et al. (1976); Zhang et al. (2021) | "There is a sense of interacting with a human being when interacting with an AI virtual assistant." |
| **Cognitive Effort / Perceptual Fluency** | Adapted from Westbrook et al. (2015); Reber et al. (2004) | "Using AI makes my work tasks feel effortless." |
| **Motivation** | Adapted from Tremblay et al. (2009) | "I feel motivated to perform well in tasks supported by AI." |
| **Performance (Self-reported)** | Adapted from Williams & Anderson (1991) | "I perform tasks efficiently and effectively." |
| **Self-Efficiacy** | Adapted from Compeau & Higgins (1995) | "I perform tasks efficiently and effectively." |

Control variables: age, gender, AI expertise level, role seniority, and industry.

**Figure 2:** Constructs, scales and example items (own illustration).

## RESULTS

Data were collected over a three-week period via an online questionnaire targeting professionals actively engaged in digital and knowledge-based work. Recruitment occurred through LinkedIn groups, Slack communities, and internal mailing lists in the tech and consulting sectors. Participants were informed that the study focused on psychological effects of AI in the workplace, particularly in relation to motivation and task engagement. Inclusion criteria required active employment in digital roles, regular exposure to AI-supported tools (e.g., ChatGPT, Copilot), and informed consent. Out of 344 responses, 297 valid cases remained after excluding incomplete entries and participants who did not meet the inclusion criteria.

The gender distribution was 54% male, 44% female, and 2% diverse. The average age was 34.7 years (SD = 7.2), with a mean of 6.8 years of professional experience (SD = 4.1). Participants represented a range of industries, including information technology (38%), consulting (26%), analytics (21%), and other sectors (15%). Self-reported frequency of AI usage varied across the sample, with 34% indicating high usage, 48% moderate usage, and 18% low usage.

To ensure measurement quality, a confirmatory factor analysis (CFA) was conducted in AMOS 29. All factor loadings exceeded 0.70 ($p < .001$), composite reliability values ranged from 0.81 to 0.90, and AVE values met or exceeded 0.50, indicating strong convergent validity. Discriminant validity was supported by the Fornell-Larcker criterion. The model exhibited good fit: $\chi^2/df = 1.87$, CFI = 0.951, RMSEA = 0.044, and SRMR = 0.041 (Hu and Bentler, 1999).

Structural equation modeling confirmed the hypothesized mediation structure. AI usage negatively affected perceived social presence ($\beta = -0.42$) and cognitive effort ($\beta = -0.38$), which in turn positively predicted motivation ($\beta = 0.35$ and $\beta = 0.31$). Motivation emerged as the strongest predictor of performance ($\beta = 0.58$).

| Path | Std. Coefficient (β) | SE | 95% CI | p-value | Hypothesis |
|---|---|---|---|---|---|
| H1a: AI Usage → Social Presence | -0.42 | 0.05 | [-0.51, -0.33] | < .001 | Supported |
| H1b: AI Usage → Cognitive Effort | -0.38 | 0.06 | [-0.49, -0.27] | < .001 | Supported |
| H2a: Social Presence → Motivation | 0.35 | 0.05 | [0.25, 0.45] | < .001 | Supported |
| H2b: Cognitive Effort → Motivation | 0.31 | 0.05 | [0.21, 0.42] | < .001 | Supported |
| H3: Motivation → Performance | 0.58 | 0.04 | [0.49, 0.67] | < .001 | Supported |

**Figure 3**: Direct effects (own illustration).

Indirect effects confirmed full mediation: AI usage influences performance only through psychological mechanisms rather than direct functional disruption.

An exploratory moderation analysis revealed that technological self-efficacy buffered the negative impact of AI on motivation. Participants with low efficacy showed a strong negative path from AI usage to motivation ($\beta = -0.33$, $p < .01$), while the path was weaker and non-significant in the high-efficacy group ($\beta = -0.12$). A chi-square difference test supported the moderating role ($\Delta\chi^2 = 6.12$, $p < .05$).

Overall, these results validate the proposed model and highlight that AI integration affects work not ownly operationally but also psychologically. The role of motivation as a central driver, shaped by both social and cognitive perceptions, underlines the importance of designing AI systems and workplace strategies that preserve intrinsic engagement and human agency.

## DISCUSSION AND LIMITATIONS

This study aimed to uncover how AI integration in knowledge-intensive work environments impacts psychological mechanisms such as motivation and performance. Drawing from the High-Performance Cycle (Locke and Latham, 2002) and informed by theories of social presence, cognitive effort, and perceptual fluency, the results affirm the model's validity: AI usage lowers perceived social presence and cognitive engagement, which in turn reduces motivation - an essential driver of self-reported performance. These findings contribute to a more nuanced view of AI's role in the workplace, emphasizing its psychological effects rather than solely functional outcomes. AI does not diminish performance directly but alters task perception and experience in ways that indirectly weaken motivational drivers.

Additionally, individuals with higher technological self-efficacy were less susceptible to these effects, suggesting that perceived competence may mitigate the motivational erosion associated with automation - an insight aligned with competence-based theories of motivation (Deci and Ryan, 2000).

Theoretically, this work expands the High-Performance Cycle into AI-mediated contexts by showing how technology influences core motivational processes such as goal engagement and feedback. It also demonstrates that social presence, often overlooked in performance modeling, plays a vital mediating role. Furthermore, the findings support fluency-effort trade-off theories, as reduced cognitive challenge - while seemingly beneficial - can decrease intrinsic motivation. These elements together create a framework for future studies that explore the relational and emotional dynamics of human-AI interaction.

From a practical standpoint, the results suggest that organizations should consider psychological as well as technical criteria when integrating AI. While automation may improve productivity, it may also diminish perceived meaning and responsibility in work. Companies should proactively preserve motivational integrity by embedding feedback loops, supporting hybrid workflows, and fostering digital confidence through training. The moderating effect of technological self-efficacy indicates that targeted competence-building could serve as a buffer against unintended motivational fallout. Design implications also emerge: AI systems that maintain interpersonal cues or modulate difficulty dynamically may sustain engagement more effectively than overly fluent, impersonal interfaces.

Ethically, these findings urge a broader view of responsible AI. When systems reduce interpersonal and cognitive involvement, they risk undermining work's meaningfulness. Psychological safety, motivational fairness, and inclusivity in digital transformation must be central to organizational ethics. Disparities in digital readiness could exacerbate motivational disengagement, particularly among employees with limited tech experience. Thus, ethical AI is not just a question of compliance or transparency, but a human-centered commitment to preserve dignity, agency, and equitable opportunity in evolving work settings.

Despite these contributions, the study has limitations. Its cross-sectional design restricts causal inference, and self-report measures, though validated, may introduce bias. The generalizability of findings is also constrained by the self-reported nature of AI usage and the heterogeneity of systems included.

Demographic variables such as age, gender, and professional experience were collected but not modeled as control variables in the interest of parsimony. Future research could examine whether such factors interact with AI-related perceptions or moderate motivational effects in specific subgroups.

While the moderation analysis yielded promising insights, it was exploratory and should be interpreted cautiously. Future research would benefit from longitudinal data, objective performance indicators, and more granular distinctions between AI technologies to refine our understanding of how – and for whom – AI changes the experience and outcomes of work.

## CONCLUSION

This study set out to explore how the integration of AI into knowledge-intensive work environments affects employee motivation and performance. Grounded in the High-Performance Cycle and enriched by theories of social presence, cognitive effort, and perceptual fluency, we developed and empirically tested a path model involving key psychological mediators.

These findings provide compelling evidence that AI usage, while potentially enhancing efficiency, can unintentionally undermine motivational mechanisms by reducing perceived social connection and diminishing cognitive investment. These effects cascade through lower motivation, ultimately weakening performance outcomes. Importantly, individuals with higher technological self-efficacy appear less susceptible to these effects, offering a valuable avenue for organizational intervention.

From a theoretical perspective, the study extends established motivational frameworks into the realm of AI-mediated work, demonstrating that technology shapes not only what we do, but how we feel about what we do. Practically, it underscores the need for human-centered design and implementation strategies that take into account the psychological consequences of automation.

Looking forward, future research should explore these dynamics over time, in collaborative team contexts, and across different types of AI systems. The goal is not to resist automation, but to integrate it in ways that sustain human agency, engagement, and meaning. In doing so, we move closer to a truly intelligent future, one that is not only artificial, but also deeply human.

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