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Yasmine Wafa and Justin Longo *

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Performance Management for Remote Workers: Not "What Are Your Employees Doing?" but Rather "How Are Your Employees Doing?"

Yasmine Wafa [1] and Justin Longo [2,*]

[1] Post-doctoral Researcher, Johnson Shoyama Graduate School of Public Administration, University of Saskatchewan, Saskatoon, Canada

[2] Associate Professor, Johnson Shoyama Graduate School of Public Policy University of Regina, Regina, Canada

* Correspondence: justin.longo@uregina.ca

Abstract

The shift to remote and hybrid work has exposed the limitations of traditional performance management systems, which often rely on physical presence or intrusive surveillance rather than outcome-based evaluation. This paper asks how AI-driven performance management can be designed to address the documented challenges of tele-working while safeguarding employee autonomy, fairness, and well-being. The study integrates a comprehensive literature review on AI capabilities with empirical evidence from a sequential mixed-methods study of Canadian public servants, comprising machine learning analysis of over 205,000 tweets, document analysis of federal and provincial teleworking policies, a survey of 176 public servants analyzed using logistic regression, and semi-structured interviews with Government of Canada employees. Grounded in socio-technical theory and the Theory of Planned Behavior, the findings reveal that organizational support, workplace socialization, and attitudes are stronger predictors of teleworking success than digital skills or monitoring, while isolation functions as a measurable risk factor. These empirical patterns are mapped to specific AI capabilities to produce a socio-technical framework organized around three interdependent layers: technological, organizational, and human-centered. The paper contributes an empirically grounded alternative to purely speculative treatments of AI in performance management, offering design requirements derived from what remote workers actually experience rather than from technological possibilities alone.

Keywords: artificial intelligence (AI); remote and hybrid work; performance management; ethical AI; socio-technical systems; employee well-being; Canadian public service; theory of planned behavior

1. Introduction

The evolution of teleworking has emerged as a defining feature of modern work environments, driven by rapid digital transformation and growing demand for workplace flexibility. By enabling employees to fulfill professional responsibilities beyond traditional office settings, teleworking has transformed organizational structures, eliminated geographical constraints, reduced operational costs, and improved work–life balance (Dutta & Mishra, 2025). Initially adopted selectively, teleworking became widespread during the COVID-19 pandemic, demonstrating its viability as a long-term strategy across diverse industries. In today's digital economy, teleworking is a crucial enabler of digital transformation, reshaping workforce management, operational efficiency, and organizational culture (Baki et al., 2023).

Despite its strategic benefits, teleworking presents substantial challenges for organizations, particularly in performance management, which requires sustained employee engagement, fair evaluation, and effective oversight. In the post-COVID era, teleworking has encountered political and

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cultural pushback as well (Braesemann et al., 2022). Traditional models, designed for co-located teams, often fail in remote environments, where productivity must be assessed without direct observation. Many current approaches to performance management rely either on intrusive surveillance—such as keystroke logging or continuous webcam monitoring, which erodes trust and increases stress—or on infrequent and vague metrics that provide limited actionable insights (Aguinis & Burgi-Tian, 2021; Koeszegi, 2024; Kulkarni et al., 2024; Mabaso & Manuel, 2024; Mkhize & Lourens, 2025). As a result, scholars and practitioners advocate for trust-centered, outcome-focused approaches that emphasize employee autonomy, engagement, and overall well-being (Ball, 2010; Deloitte, 2023).

Emerging solutions highlight AI-driven performance management as a viable approach for addressing these challenges. AI-driven analytics have the capacity to identify performance trends, deliver personalized feedback in real time, foster skill development, and align employees' efforts with organizational goals, while simultaneously protecting privacy and supporting psychological well-being (Kalischko & Riedl, 2021; Deloitte, 2023). Unlike traditional oversight tools, AI can focus on outcomes rather than surveillance, monitor collaboration dynamics, and recognize qualitative contributions such as problem-solving, creativity, and teamwork.

This paper introduces an AI-driven, socio-technical performance management framework designed for remote and hybrid work environments. What distinguishes this contribution from purely conceptual treatments is its empirical grounding: the framework's design requirements are derived from a sequential mixed-methods study of teleworking in the Canadian public service (Wafa, 2024), comprising machine learning analysis of over 205,000 tweets, document analysis of federal and provincial government teleworking policies, an online survey of 176 public servants, and semi-structured interviews with Government of Canada employees. These empirical findings establish what remote workers, and their managers, actually experience, struggle with, and need—providing the evidentiary base from which the speculative AI-driven framework is built.

The logic of the paper can be expressed as: here is what the evidence tells us about the real challenges and success factors for remote performance management; here is what the literature tells us AI can do; and here is how a socio-technical framework could integrate those AI capabilities to address the empirically documented needs. By combining a comprehensive literature review on AI capabilities with empirical evidence from the Canadian public service, and by integrating socio-technical theory with the Theory of Planned Behavior, this paper offers a framework that is speculative in its forward-looking design but grounded in real-world evidence.

2. Literature Review

The rapid adoption of teleworking, driven by digital transformation, has fundamentally reshaped traditional work structures and management practices. As remote and hybrid models become standard across industries, organizations face growing challenges in sustaining productivity, engagement, and accountability in dispersed environments. Conventional performance management approaches—historically grounded in direct supervision and physical presence—are increasingly misaligned with the autonomy, flexibility, and asynchronous workflows characteristic of remote work.

This literature review examines the intersection of teleworking, digital transformation, and performance management, highlighting structural, cultural, and technological shifts that redefine organizational strategies. Special attention is given to the challenges of monitoring and evaluating employee contributions in virtual contexts, where reliance on surveillance-based tools can erode trust, engagement, and well-being. In response, artificial intelligence (AI) is emerging as a transformative enabler, offering the potential to enhance performance management through greater efficiency, bias reduction, and actionable, data-informed insights. By integrating socio-technical principles, AI frameworks can support both organizational goals and employee-centered outcomes, fostering inclusion, fairness, and resilience in remote and hybrid work settings.

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2.1. Teleworking and Digital Transformation

Teleworking refers to flexible work arrangements in which employees operate remotely from traditional office locations while leveraging digital communication and collaboration technologies (Wang et al., 2021). Despite its strategic advantages, teleworking is interpreted variably across research and practice, with related concepts including telecommuting, hoteling, flexi-places, and virtual workplaces (Bailey & Kurland, 2002; De Vries et al., 2019; Brynjolfsson et al., 2020).

Although teleworking has existed for decades, its adoption accelerated significantly during the COVID-19 pandemic, which forced organizations to implement remote work at unprecedented scale. Hybrid models combining remote and on-site work have since become dominant, particularly among large organizations (GitLab, 2021; Microsoft, 2021; Statistics Canada, 2021). These shifts have profound implications for workforce management, requiring approaches that maintain engagement, fairness, and well-being without relying on intrusive oversight.

Digital transformation, defined as the strategic integration of technologies across organizational processes, is a key enabler of effective teleworking. Tools such as cloud computing, workflow automation, and AI-driven analytics allow organizations to coordinate work, provide continuous feedback, and evaluate performance in ways that do not depend on physical presence (Madanchian et al., 2024). Beyond technology, successful digital transformation requires trust-based organizational cultures and adaptive leadership that balance performance expectations with employee autonomy and well-being (Hossain et al., 2025).

Teleworking and digital transformation are mutually reinforcing. Remote work drives organizations to invest in scalable infrastructure, adopt collaborative platforms like Microsoft Teams, Slack, and Zoom, and integrate AI-powered analytics for workflow optimization and decision-making (Mancl & Fraser, 2023; Microsoft, 2025a–2025c). These developments highlight the shift from office-centric structures to digitally mediated, flexible workplaces.

Despite these advances, teleworking introduces persistent challenges. Assessing productivity, sustaining collaboration, and preventing burnout require performance management systems aligned with digital workflows and human-centered principles. Traditional approaches focused on presence and manual oversight are increasingly inadequate. AI-enabled performance management offers solutions through outcome-oriented, adaptive, and personalized frameworks. When integrated with socio-technical strategies, AI supports transparency, fairness, and employee well-being while enhancing engagement, development, and organizational resilience.

In summary, the literature underscores that the future of performance management in remote and hybrid work is not defined solely by physical location but by the integration of technology, organizational culture, and human-centered management. AI-driven, socio-technical frameworks provide a conceptual foundation for developing performance management systems that are ethical, inclusive, and effective in digitally mediated work environments.

2.2. Challenges in Performance Management for Remote Work

Being physically apart limits managers' ability to gauge engagement, monitor task progress, and understand team dynamics through direct observation or informal interactions (Mkhize & Lourens, 2025). This can result in insufficient oversight, risking misalignment and underperformance, or excessive scrutiny, manifesting as micromanagement that undermines trust and autonomy. Outcome-based approaches, which emphasize measurable outputs and goal attainment, partially address these challenges. However, overreliance on quantitative indicators may overlook qualitative aspects of work, such as collaboration, creativity, and discretionary effort. Transparent expectations and adaptive management practices are therefore essential to maintain alignment while supporting employee autonomy and engagement (Aguinis & Burgi-Tian, 2021; Gibbs et al., 2023).

Lack of Direct Oversight. Physical separation reduces managers' ability to assess engagement, task progress, and team dynamics through observation and informal cues (Mkhize & Lourens, 2025). This can lead to insufficient oversight, risking misalignment and underperformance, or excessive scrutiny, manifesting as micromanagement that erodes trust and autonomy (Mkhize & Lourens, 2025).

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Micromanagement Risks. Remote work can exacerbate tendencies toward micromanagement. Managers, facing limited visibility, may overcompensate by closely scrutinizing tasks, undermining employee morale, engagement, and psychological safety (Bailey & Kurland, 2002; Mkhize & Lourens, 2025). Balancing oversight with autonomy is critical to sustaining trust and motivation in distributed teams.

Communication Barriers. Digitally mediated communication introduces structural constraints. Asynchronous messaging, absence of non-verbal cues, and limited spontaneous interactions can reduce clarity, slow decision-making, and hinder trust-building (Bailey & Kurland, 2002; Mkhize & Lourens, 2025). Informal knowledge sharing and team cohesion, essential for problem-solving and innovation, are harder to maintain in remote contexts.

Employee Isolation and Well-being. Remote and hybrid work can lead to social isolation, reduced belonging, and detachment from organizational culture, negatively affecting engagement, motivation, and performance (Bailey & Kurland, 2002; Mkhize & Lourens, 2025). Prolonged isolation increases stress and burnout risk, highlighting the importance of strategies to maintain connection and support employee well-being.

2.3. AI-Driven Performance Management: Capabilities, Solutions, and Limitations

Building on the challenges identified above, AI-driven performance management offers targeted capabilities to address the unique constraints of remote and hybrid work environments. By providing continuous, data-informed evaluation, adaptive feedback, and ethical oversight, AI enhances managerial capacity while supporting employee autonomy, engagement, and well-being. At the same time, these AI systems have inherent limitations and require careful ethical and organizational governance. The following subsections present solutions aligned with the five key dimensions identified in the literature: automated productivity tracking, sentiment analysis and employee well-being, adaptive goal-setting and personalized feedback, enhancing fairness and reducing bias, and ethical considerations and employee trust.

2.3.1. Automated Productivity Tracking

Reduced direct oversight and the risk of micromanagement, central challenges in remote work, are addressed by AI-powered analytics that aggregate task completion, workflow patterns, and team interactions. These AI-driven systems offer managers real-time, comprehensive insights into both individual and team performance, allowing for timely, proactive interventions without resorting to intrusive supervision (Wang & Panesar, 2022; Microsoft, 2025a–2025c; Asana, 2025a–2025c; Culture Amp, 2025; BambooHR, 2025). By moving the focus away from continuous oversight toward data-informed decision-making, AI fosters accountability while maintaining employee autonomy (Mkhize & Lourens, 2025).

AI can also help capture aspects of qualitative performance that traditional metrics often miss. Natural language processing (NLP) can analyze project updates, emails, and collaborative documents to highlight contributions to problem-solving, knowledge sharing, and collaborative engagement (Tausczik & Pennebaker, 2010; Mäntylä et al., 2018). Organizational network analysis (ONA) identifies patterns of interaction and collaboration, providing indirect insights into teamwork quality and information flow (Goodings et al., 2024; Humanyze, 2025). Despite these advances, AI systems remain limited in their ability to directly assess qualitative contributions, as they can only infer aspects of performance through available data proxies. Complex attributes such as creativity, strategic thinking, and nuanced problem-solving cannot be fully captured through algorithmic analysis alone. Human judgment remains indispensable for interpreting AI-generated insights and integrating them into comprehensive and context-sensitive performance evaluations.

2.3.2. Sentiment Analysis and Employee Well-being

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Communication barriers, social isolation, and well-being concerns in remote work are mitigated through AI-enabled sentiment analysis and well-being monitoring. NLP systems analyze textual data from emails, messaging platforms, and collaboration tools to detect emotional cues, enabling managers to identify stress, disengagement, or burnout early (Mäntylä et al., 2018; Kulkarni et al., 2024). AI-driven mental health tools, including conversational agents like Woebot and Wysa, as well as platforms such as Spring Health, Lyra Health, and Headspace Care, deliver evidence-based interventions grounded in cognitive behavioral therapy, mindfulness, and personalized recommendations (Fitzpatrick et al., 2017; Inkster et al., 2018; Callahan et al., 2024; Lee et al., 2025). Scheduling and productivity tools, including Microsoft Viva Insights, Clockwise, and Reclaim.ai, optimize workloads, protect focus time, and reduce burnout risk (Clockwise, 2023; Microsoft, 2025a–2025c; Reclaim.ai, 2025). Despite these benefits, AI-based well-being interventions must be opt-in, ethically designed, and transparent to avoid perceptions of surveillance. Human-centered leadership and organizational culture remain critical to reinforce genuine support, trust, and social connection (Ashdown, 2018).

2.3.3. Adaptive Goal-Setting and Personalized Feedback

AI enables dynamic, adaptive goal-setting and continuous personalized feedback, addressing challenges in alignment, performance clarity, and managerial oversight. By analyzing individual progress, peer performance, and workload distribution, AI systems recalibrate goals to enhance motivation, prevent overload, and support engagement (Rockmann & Pratt, 2015; Davenport & Beier, 2020; Jarrahi et al., 2021). Continuous, context-sensitive feedback replaces static, infrequent reviews, providing actionable insights that facilitate learning and skill development (Pulakos et al., 2015; Cosa & Torelli, 2024). Key limitations include the risk of depersonalized feedback when AI systems excessively automate performance evaluation processes. Overreliance on algorithmic outputs may diminish opportunities for meaningful dialogue, thereby weakening empathy, relational judgment, and contextual interpretation. Sustained human oversight is therefore essential to ensure that performance assessments remain balanced, fair, and sensitive to individual circumstances (Buckingham & Goodall, 2015; Dastin, 2018; Leicht-Deobald et al., 2022).

2.3.4. Enhancing Fairness and Reducing Bias

AI has the potential to mitigate human evaluation biases and support equitable performance management. AI can minimize biases such as favoritism, halo effects, or recency bias by employing consistent, data-driven evaluation criteria (Raisch & Krakowski, 2021). Platforms like Workday and Eightfold AI enable consistent evaluations across employees, while algorithmic audits help uncover systemic inequities in promotions, recognition, or compensation (Binns et al., 2018; Raghavan et al., 2020). Nevertheless, biases can persist through unrepresentative training data or flawed algorithm design. AI should augment not replace human judgment, ensuring contextual interpretation, empathy, and procedural fairness (Glikson & Woolley, 2020; Langer et al., 2021; Mehrabi et al., 2021).

2.3.5. Ethical Considerations and Employee Trust

The use of AI in performance management raises critical ethical considerations, particularly regarding privacy, consent, data security, and algorithmic accountability. Maintaining trust requires transparency about what data are collected, how they are analyzed, and how outputs inform decisions (Binns et al., 2018; Cowgill, 2018; Yanamala, 2023). Employees must have opportunities to participate in AI system selection, customization, and evaluation to reduce power asymmetries and reinforce procedural fairness (Shrestha et al., 2019). Human oversight is essential to ensure that AI complements managerial judgment rather than replacing relational and ethical decision-making. AI systems must operate within ethical and governance frameworks that uphold organizational values, protect autonomy, and sustain legitimacy (Floridi et al., 2018; European Commission, 2019; John et al., 2022).

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The AI capabilities reviewed here represent a range of possibilities whose real-world value depends on whether they address documented, demonstrated needs—not merely theoretical gaps. The empirical evidence presented below in Section 4 provides exactly this grounding, establishing what remote workers actually experience and what the data reveal about the conditions under which AI-driven performance management could make a meaningful difference.

3. Theoretical Framework

This paper integrates two complementary theoretical lenses—socio-technical theory and the Theory of Planned Behavior—to guide the development of an AI-driven performance management framework. Socio-technical theory provides the design architecture for the framework, while the Theory of Planned Behavior informs the human-behavioral layer that determines whether the framework will be adopted and sustained.

3.1. Socio-Technical Theory

This research is grounded in socio-technical theory, which highlights how social and technical systems are interdependent in influencing organizational performance (Trist, 1993). In remote and hybrid work, performance outcomes are influenced not only by advanced AI tools such as productivity tracking, adaptive feedback, and sentiment analysis but also by human factors (motivation, trust, engagement), organizational structures (feedback loops, goal alignment), and environmental conditions (regulatory, cultural, and ethical contexts). Socio-technical theory provides a robust lens for examining how AI-enabled performance management systems can enhance performance while balancing efficiency, fairness, and employee well-being.

The framework maps AI solutions to four interdependent subsystems. The *technical subsystem* encompasses AI-driven platforms and digital infrastructures—automated productivity tracking, sentiment analysis, adaptive goal-setting, and fairness-enhancing tools. The *personnel subsystem* considers the human dimension, including employee skills, motivation, attitudes toward AI, and expectations around fairness, recognition, and work–life balance. The *organizational subsystem* addresses structures, policies, and feedback mechanisms that determine how AI solutions are integrated into practice—including whether decentralized dashboards empower employees or centralized algorithmic assessments disempower them. The *environmental subsystem* encompasses external regulatory, cultural, and ethical factors that shape the deployment of AI systems, including data protection regulations, cultural norms surrounding surveillance, and broader societal expectations (Bélanger et al., 2013; European Commission, 2019; Zuboff, 2023).

3.2. Theory of Planned Behavior as a Complementary Lens

The empirical study that grounds this paper employed the Theory of Planned Behavior (TPB) as its primary theoretical framework. TPB posits that behavioral intention—in this case, the intention to engage productively in telework—is shaped by three constructs: attitudes toward the behavior, subjective norms (perceived social pressure), and perceived behavioral control (confidence in one's ability to perform the behavior) (Ajzen, 1991).

TPB complements socio-technical theory by addressing a question that system design alone cannot answer: whether employees and managers will actually engage with AI-driven performance management tools. While socio-technical theory focuses on how to build the framework (system design), TPB focuses on whether people will use it (adoption behavior). The empirical findings presented in Section 4 are structured around TPB constructs, and these constructs map naturally onto the socio-technical subsystems—attitudes and perceived behavioral control relate to the personnel subsystem, while subjective norms connect to both the organizational and environmental subsystems.

3.3. Integrating the Two Frameworks

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The integration of socio-technical theory with TPB provides a dual analytical lens: socio-technical theory supplies the design architecture for the AI-driven performance management framework, specifying how technical, organizational, personnel, and environmental subsystems must align; TPB informs the human-behavioral layer, identifying the attitudinal and normative conditions under which employees are likely to adopt and benefit from such a framework. As the empirical evidence will demonstrate, attitudes toward teleworking and social norms overwhelmingly shape telework preferences—while perceived behavioral control (digital skills and technology access) shows no independent effect. This finding has direct implications for framework design: the framework must address not just technical capabilities but the cultural and attitudinal conditions that determine adoption.

4. Empirical Foundation: Teleworking in the Canadian Public Service

This section presents the empirical evidence that grounds the proposed framework. The findings are drawn from a sequential mixed-methods study of teleworking in the Canadian public service (Wafa, 2024), organized not by method but by thematic relevance to the performance management challenges identified in the literature review.

4.1. Research Design and Methods

The study employed a sequential mixed-methods design comprising four complementary approaches. First, a machine learning and big data analysis examined 205,204 tweets from 2022 using RapidMiner, applying sentiment analysis, frequency analysis, and Latent Dirichlet Allocation (LDA) topic modeling to capture broad public discourse on teleworking. Second, a document analysis assessed federal, provincial, and territorial government teleworking policies using NVivo and RapidMiner for sentiment and thematic analysis, capturing the employer and policy perspective. Third, an online survey of 176 Canadian public servants (federal and provincial) employed binary logistic regression, Pearson correlation, and Chi-square analysis to test Theory of Planned Behavior constructs quantitatively. Fourth, six semi-structured interviews with Government of Canada public servants (five managers or policymakers and one employee) across four federal departments provided rich qualitative depth.

The sequential logic is important: each method informed the next, building from broad public sentiment to the policy and employer perspective, then to targeted employee data, and finally to deep individual experience. This triangulation across methods and data sources strengthens the evidentiary base from which the framework's design requirements are derived. For full methodological detail, see Wafa (2024).

4.2. What Remote Workers Actually Experience: Key Findings

The findings are organized thematically around the performance management challenges identified in Section 2.2. For each theme, evidence is triangulated across the four methods where possible.

4.2.1. The Performance Visibility Problem

The literature review identified lack of direct oversight and micromanagement risks as central challenges in remote performance management (Section 2.2). The empirical evidence confirms these challenges while revealing an important nuance: employees and managers alike recognize that visibility into work can be achieved without surveillance, and that organizational support matters far more than monitoring.

In the interviews, performance monitoring was cited as a key driver of return-to-office mandates. One participant noted: "People can monitor employees better than if they are working from home. I think that would be the main reason." Yet another participant offered a counter-narrative: "People now recognize that you do not have to see people to know they are doing work…

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it forces a conversation about efficiency and effectiveness." This tension between surveillance-based and outcome-based approaches was a recurring theme, with interviewees identifying outcome-oriented management as a critical success factor. Managers who adapted their leadership from presence-based to results-based evaluation were seen as more effective.

The survey data reinforced this pattern. Support emerged as the single strongest predictor of better teleworking arrangements, with an odds ratio of 6.793—meaning that as perceived organizational support increased by one unit, the odds of achieving better teleworking arrangements increased nearly sevenfold. This finding challenges surveillance-first approaches to remote performance management and suggests that the quality of managerial engagement matters more than the quantity of monitoring.

The machine learning analysis corroborated these findings at the population level. In topic modeling of over 205,000 tweets, "productivity" emerged as the number-one critical success factor for teleworking (of 30 factors identified), and "support" ranked third. Public discourse centers on outputs and enablement, not surveillance.

Implication for framework design: There is a documented need for performance management tools that provide visibility into work progress and outcomes without resorting to surveillance—exactly what AI-driven outcome-focused analytics promises.

4.2.2. Communication, Collaboration, and Isolation

The literature review identified communication barriers and employee isolation as significant challenges (Section 2.2). The empirical evidence demonstrates that isolation is not merely a subjective complaint but a measurable risk factor, while socialization functions as a measurable protective factor.

The survey found that isolation had a statistically significant negative effect on teleworking quality (odds ratio = 0.871), while workplace socialization had a strong positive effect (odds ratio = 3.973). These are not trivial findings: socialization increased the odds of better teleworking arrangements by nearly four times, establishing it as one of the most consequential variables in the model.

The interviews added qualitative depth to these statistical patterns. Marital status emerged as an important contextual factor: married or partnered public servants had built-in socialization, while single employees reported greater isolation challenges. As one participant reflected: "I certainly feel for my single colleagues because I am happily married and have two kids. I have more than enough interaction with people." Technology both helped and hindered communication: video conferencing was described as "better for many employees because only one person could speak at one time" (more inclusive for those with hearing impairments), but the absence of spontaneous encounters limited serendipitous idea exchange.

In the Twitter analysis, "communication" ranked 25th of 30 critical success factors—relatively low, suggesting it may be taken for granted in public discourse rather than seen as a primary concern. Meanwhile, the document analysis found that every jurisdiction identified communication and collaboration as both a challenge and a success factor for teleworking, underscoring its dual nature.

Implication for framework design: The evidence demonstrates that isolation is a measurable risk factor, socialization is a measurable protective factor, and communication technology is necessary but insufficient. AI-driven sentiment analysis and well-being monitoring could detect isolation and disengagement signals before they become crises.

4.2.3. Fairness, Equity, and Policy Consistency

The literature review discussed AI's potential to enhance fairness and reduce bias in performance evaluations (Section 2.3.4). The empirical evidence reveals that fairness concerns in remote work extend well beyond evaluation bias to encompass systemic policy inconsistencies, gendered impacts, and a striking disconnect between employer rhetoric and employee experience.

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In the interviews, fairness was a pervasive concern. The lack of uniform teleworking policies across federal departments created inter-departmental competition for employees. As one participant described: "None of us have the same stories. None of us have the same obligations." Departments used telework arrangements as recruitment inducements—"What is the teleworking agreement if I am going to your department? Is it full-time? Okay, I will work with you. If not, I am not coming"—creating perceived inequity across the public service.

Gender disparities in teleworking impacts were documented through the interviews. Women bore disproportionate domestic burdens during telework. One participant reported: "All the studies show that women, even those working full time out of the house, do more work at home than their spouses." A male manager corroborated: "Most of my female co-workers took the brunt of that new role and expectations. Many men returned to the office or had a designated space, for example, in the house, whereas women had to do this in the kitchen or wherever they fit."

The survey found that education (odds ratio = 2.0) and marital status significantly predicted teleworking quality, suggesting that existing demographic advantages amplify teleworking benefits unevenly. Meanwhile, the document analysis revealed that government teleworking policies were 97–99% positive in sentiment across all jurisdictions—a striking disconnect from the mixed challenges reported by actual employees in the survey and interviews.

Implication for framework design: AI-driven evaluation tools could standardize performance criteria across departments and locations, reduce subjective bias, and flag emerging inequities in workload distribution or recognition patterns—but only if designed with explicit awareness of these documented equity gaps.

4.2.4. Well-being, Work–Life Balance, and the "Always-On" Problem

The literature review identified sentiment analysis and well-being monitoring as key AI capabilities for remote work (Section 2.3.2). The empirical evidence reveals that well-being in telework is not a binary outcome but a dynamic balance that shifts with individual circumstances, organizational policy, and the broader political environment.

The survey found that work–life balance had a positive but modest effect on teleworking quality (odds ratio = 1.13). The interviews provided crucial context for this modest statistical effect by revealing the complexity of well-being dynamics. Teleworking reduced some stressors—commuting, office noise, self-consciousness about breaks—but created new ones, including blurred boundaries, "always-on" culture, and lack of social interaction. One participant captured this duality: "It has been much better for my mental health. My physical health is definitely worse just because I do not really do any exercise."

The political dimension of well-being also emerged. Mandated return-to-office policies undermined well-being gains built over three years of remote work. As one participant described: "We started to develop a way to carry on our work online as much as possible and now we are destroying the culture that has been built." In the Twitter analysis, "wellness support" ranked 10th and "work–life balance" ranked 12th among 30 critical success factors, indicating these are recognized needs in public discourse. The document analysis found that multiple jurisdictions cited work–life balance as both a benefit and a challenge of teleworking.

Implication for framework design: AI-driven well-being monitoring must be sensitive to this complexity—adaptive, opt-in, and attentive to the specific stressors documented here, rather than relying on crude binary indicators.

4.2.5. The Role of Attitudes, Norms, and Organizational Culture

The theoretical framework (Section 3) posited that TPB constructs would influence telework adoption. The empirical evidence not only confirms this but produces a surprising finding that has direct implications for framework design.

The survey's TPB analysis yielded the equation: Logit = β_0 + 6.293 Attitudes + 56.008 Norms + 0 PBC + ε. Attitudes (β = 6.293) and social norms (β = 56.008) were powerful predictors of teleworking

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preference. Strikingly, perceived behavioral control—encompassing digital skills and technology access—showed no independent effect in multivariate analysis, despite showing bivariate correlations. This means that once attitudes and norms are accounted for, having the technical skills and tools to telework does not independently predict whether an employee prefers teleworking.

The interviews reinforced the importance of attitudes: positive attitude was described as "one of the most important factors determining perception and effectiveness" of teleworking. The interview data on organizational culture revealed that teleworking can disrupt established organizational norms and identity but also presents an opportunity to redefine norms and values using technology. The Twitter analysis showed overall positive public sentiment (32% positive versus 4.6% negative, when determinable), but 62% of tweets had indeterminate sentiment—suggesting a large, undecided population whose attitudes could be shaped.

Implication for framework design: The AI-driven framework must address not just technical capabilities but the attitudinal and cultural conditions for adoption. Participatory design, transparency, and demonstrated value are preconditions—not afterthoughts. The empirical findings map systematically to framework design requirements, as shown in Table 1.

Table 1. Mapping of empirical findings onto framework design requirements.

Empirical Finding	Framework Design Requirement
Performance visibility problem: managers need insight without surveillance	AI-driven outcome-focused analytics with transparency safeguards
Isolation as measurable risk; socialization as protective factor	Proactive well-being monitoring with opt-in sentiment analysis
Fairness gaps across departments, demographics, and geography	Standardized, bias-audited evaluation criteria with equity dashboards
Complex well-being dynamics: not binary, con-text-dependent	Adaptive, personalized well-being support with privacy by design
Attitudes and norms drive adoption more than technical skill	Participatory design, demonstrated value, hu-man-centered governance

5. Toward a Socio-Technical, AI-Driven Performance Management Framework

Building on the empirical evidence from Section 4 and the AI capabilities reviewed in Section 2.3, this section proposes an integrated framework for AI-driven performance management in remote and hybrid work. Each element of the framework is explicitly tied to documented challenges and evidence-based design requirements.

5.1. Framework Architecture

The framework integrates three interdependent layers, mapped onto the socio-technical subsystems:

Technological Layer (Technical Subsystem). This layer encompasses the AI-driven tools that form the analytical foundation of the framework. Outcome-focused AI analytics respond to the performance visibility problem documented in Section 4.2.1, providing managers with real-time dashboards that aggregate task completion, workflow patterns, and collaboration metrics—without keystroke logging or webcam monitoring. NLP-based sentiment and engagement monitoring responds to the isolation and well-being evidence from Sections 4.2.2 and 4.2.4, detecting team-level disengagement trends through analysis of communication patterns rather than content. Algorithmic fairness tools and bias auditing respond to the equity gaps documented in Section 4.2.3, applying standardized evaluation criteria across departments and geographies. Adaptive goal-setting engines respond to the work–life balance complexity from Section 4.2.4, recalibrating individual goals based on workload, team capacity, and contextual circumstances.

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Organizational Layer (Organizational Subsystem). This layer provides the governance and process infrastructure that determines whether the technological tools produce equitable outcomes. Standardized, transparent performance management policies across departments respond to the fairness and consistency findings from Section 4.2.3, where inter-departmental competition and policy inconsistency created perceived inequity. Feedback loops integrating AI insights with human judgment respond to the nuanced performance evidence from Section 4.2.1, where managers who combined outcome data with relational engagement were most effective. Manager training and support infrastructure responds to the documented need for new leadership approaches, recognizing that the survey's strongest predictor was organizational support (odds ratio = 6.793), not monitoring capability.

Human-Centered Layer (Personnel and Environmental Subsystems). This layer ensures that the framework's design and governance reflect the documented primacy of attitudes, norms, and culture in determining telework outcomes. Participatory design processes involving employees in AI system selection and governance respond to the attitudes and norms findings from Section 4.2.5, where these constructs overwhelmed perceived behavioral control. Opt-in well-being support with clear privacy safeguards responds to the "always-on" problem from Section 4.2.4, where employees described complex and context-dependent well-being dynamics. Equity-aware design addressing documented demographic disparities responds to the gender and marital status findings from Section 4.2.3, ensuring that the framework does not reproduce existing inequities.

5.2. Speculative Possibilities: How the Framework Could Operate

For each AI capability area, this section describes how it could function within the proposed framework, grounding each speculation in the empirical evidence.

Outcome-Focused AI Analytics in Practice. AI systems could aggregate task completion, workflow patterns, and collaboration metrics to give managers real-time performance dashboards—without keystroke logging or webcam monitoring. The empirical evidence supports this: the interviews showed that managers who shifted to outcome-based evaluation were more effective, and the survey found that organizational support (not monitoring) was the strongest predictor of better telework arrangements. Ethical guardrails would include transparency about what data is collected, employee access to their own analytics, and prohibition of punitive use of well-being data.

Proactive Well-being Monitoring. NLP analysis of communication patterns (not content) could detect team-level disengagement trends; opt-in chatbot-based check-ins could support individual well-being assessment. The empirical evidence supports this: isolation was a documented risk factor (odds ratio = 0.871), socialization was protective (odds ratio = 3.973), and interviewees described mental health tradeoffs in nuanced terms that a crude survey would miss. Guardrails would include opt-in participation only, aggregate reporting at the team level rather than individual surveillance, and clear separation between well-being support and performance evaluation.

Fairness-Enhancing AI. Standardized evaluation criteria could be applied consistently across departments and geographies; algorithmic audits could flag disparities in recognition, promotion, or workload distribution. The empirical evidence supports this: inter-departmental competition via differential telework policies was documented, gender-based disparities were identified, and the disconnect between government rhetoric (97–99% positive) and employee experience highlights a fairness gap that standardized tools could help close. Guardrails would include regular bias audits with diverse oversight, human review of all consequential decisions, and representation of affected groups in system governance.

Adaptive Goal-Setting. AI systems could recalibrate individual goals based on workload, team capacity, and personal circumstances—recognizing that teleworking parents, single employees, and employees in different time zones face different constraints. The survey showed that education, marital status, and work–life balance all influenced teleworking quality; the interviews documented how personal circumstances shaped the experience in ways that one-size-fits-all goal-setting cannot accommodate. Guardrails would include employee agency in goal negotiation, safeguards against

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algorithmic bias in workload distribution, and transparency in how personal circumstances inform adaptations.

5.3. What This Framework Does Not—and Cannot—Do

An honest assessment of limitations, informed by the empirical evidence, is essential.

First, the survey finding that digital skills showed no independent effect on teleworking quality (despite bivariate correlations) suggests that technology alone does not determine outcomes—organizational and cultural factors dominate. No AI framework can substitute for genuine organizational commitment to supporting remote workers.

Second, the interviews revealed that political pressure—downtown business impacts, citizen perceptions, union dynamics—drove return-to-office mandates more than performance evidence. No AI framework can override political decision-making, however robust its data.

Third, the documented disconnect between government policy rhetoric (overwhelmingly positive) and employee experience (mixed and complex) suggests that framework adoption requires genuine organizational commitment, not performative endorsement. AI tools deployed in an organizationally hostile environment will not produce the outcomes described here.

Fourth, AI tools cannot substitute for the hallway conversations, spontaneous encounters, and serendipitous idea exchange that some interviewees valued. The framework augments human connection—it does not replace it.

6. Discussion

6.1. Contributions to Theory and Practice

This paper makes three interrelated contributions. Methodologically, it demonstrates how empirical evidence from one domain—the lived experience of teleworking in the Canadian public service—can ground speculative framework design in another—AI-driven performance management. The approach bridges descriptive research (what is) and prescriptive design (what could be), providing a model for evidence-informed framework development in domains where full implementation data is not yet available.

Theoretically, the integration of socio-technical theory with the Theory of Planned Behavior provides a dual lens that captures both system design and human behavior. The empirical finding that attitudes and norms overwhelm perceived behavioral control has direct implications for implementation strategy: organizations investing in AI-driven performance management should allocate at least as much attention to cultural change, participatory design, and demonstrated value as they do to technical infrastructure.

Practically, the framework offers a structured approach for organizations transitioning from presence-based to outcome-based performance management, with each element tied to documented challenges and evidence-based design requirements rather than aspirational possibilities alone.

6.2. Implications for Policy

The empirical evidence has several implications for public sector teleworking policy. The documented inter-departmental inconsistency in telework policies argues for standardized AI-driven performance management frameworks as an equity measure—not merely an efficiency tool. The political dynamics of return-to-office mandates suggest that AI-driven performance management tools could provide the evidence base that political decision-makers currently lack, demonstrating that remote workers are productive without requiring physical presence. However, the evidence also cautions that data alone may not override political imperatives driven by downtown economic concerns or citizen perceptions. The gendered impacts of teleworking require that any AI-driven performance management framework include equity auditing as a core, not peripheral, feature. The finding that women bore disproportionate domestic burdens during telework means that

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performance evaluation systems must account for the unequal conditions under which work is performed.

6.3. Limitations and Future Research

Several limitations should be acknowledged. The empirical evidence is drawn from the Canadian public service, and generalizability to private sector organizations, other countries, or other levels of government requires further study. The AI capabilities described in Section 5 are speculative extrapolations from current technology—real-world implementation may reveal unexpected challenges in areas such as algorithmic bias, user acceptance, and organizational resistance. The survey response rate (6.4%) and interview sample (n = 6) are modest; larger-scale studies are needed to validate the design requirements derived here, though the triangulation across four methods partially mitigates this limitation. The Twitter data predates the platform's transformation under new ownership, and the applicability of social media sentiment analysis may have shifted since data collection. Future research should pilot specific elements of the proposed framework in organizational settings to test feasibility and impact. Longitudinal studies tracking the introduction of AI-driven performance management tools in remote work environments would provide crucial evidence about adoption dynamics, unintended consequences, and the sustainability of initial benefits. Comparative studies across public and private sectors, and across national contexts, would strengthen the generalizability of the framework's design principles.

7. Conclusion

This paper has argued that AI-driven performance management for remote workers must be grounded in evidence about what remote workers actually experience and need—not merely in what technology makes possible. By integrating a comprehensive literature review on AI capabilities with empirical evidence from a mixed-methods study of the Canadian public service, and by combining socio-technical theory with the Theory of Planned Behavior, the paper has proposed a framework in which each design element responds to documented challenges: the performance visibility problem, isolation and communication barriers, fairness and equity gaps, well-being complexity, and the primacy of attitudes and norms.

The empirical evidence offers a clear message. Organizational support matters more than monitoring (odds ratio = 6.793). Socialization protects while isolation harms (odds ratios = 3.973 and 0.871, respectively). Attitudes and social norms overwhelm technical skills in predicting telework outcomes (TPB equation: $\beta = 6.293$ for attitudes, $\beta = 56.008$ for norms, $\beta = 0$ for perceived behavioral control). Government rhetoric runs far ahead of employee experience (97–99% positive policy sentiment versus mixed lived reality). And political dynamics constrain what any framework can achieve.

The proposed framework takes these findings seriously. It envisions AI not as a surveillance mechanism but as a support system—one that provides performance visibility without intrusion, detects well-being risks without violating privacy, standardizes evaluation without erasing context, and adapts to individual circumstances without reinforcing inequity. Its honest assessment of limitations acknowledges that technology alone cannot solve problems that are fundamentally organizational, cultural, and political.

The question this paper poses—"How are your employees doing?" rather than "What are your employees doing?"—is not merely rhetorical. It captures a fundamental reorientation in performance management philosophy, from control to care, from surveillance to support, from compliance to development. AI-driven tools, thoughtfully designed within a socio-technical framework and grounded in empirical evidence, can help organizations make this transition. But only if the humans who design, deploy, and govern these tools commit to the same reorientation.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
COVID-19	Coronavirus Disease 2019
EPM	Electronic Performance Monitoring
HR	Human Resources
IT	Information Technology
NLP	Natural Language Processing
ONA	Organizational Network Analysis

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