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COMPARATIVE STUDY OF AI-BASED EMPLOYEE MONITORING SYSTEMS VS SELF-REPORTED PRODUCTIVITY ASSESSMENT ON EMPLOYEE WELLBEING AND JOB SATISFACTION

Tuba Akram

Lecturer, Iqra University, Karachi, Pakistan

Corresponding Author: *
Tuba Akram
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ABSTRACT

The introduction of artificial intelligence (AI) systems into the workplace has changed how productivity of employees is evaluated. Monitoring employee productivity with AI systems that involve algorithmic surveillance, predictive performance models and real-time behaviour monitoring systems is increasingly becoming common more than the use of self-reported productivity assessment. Such systems are advantageous in terms of efficiency, objectivity and scalability but are harmful to the wellbeing, satisfaction, autonomy and psychological safety of workers. This paper presents the critical comparative analysis of AI-based systems and self-reported productivity measures in the light of the Job Demands-Resources (JD-R) model. The article is quantitative and statistical tests the impacts of such systems on employee wellbeing and job satisfaction in various organisational settings via SPSS. The results prove the hypothesis that surveillance by AI improves the perceived job demand, technostress and surveillance anxiety, which initiates poor employee wellbeing and job satisfaction. On the other hand, the methods of self-reported productivity promote the sense of autonomy, trust and psychological empowerment which positively affect the wellbeing of employees. This paper is a contribution to the literature because it synthesises the socio-technical systems theory, algorithmic management views, and wellbeing models at the workplace and provides empirical recommendations that organisations can adopt in optimizing the performance of technology and people-centered work design.

Keywords: *Artificial Intelligence (AI), employee monitoring systems, employee wellbeing, job satisfaction, job demands–resources (JD-R) model*

1. INTRODUCTION

1.1 Background of the Study

The contemporary workplace is undergoing a radical, multidimensional digital transformation that is inspired by rapid interconnected changes in artificial intelligence (AI), machine learning (ML), big data analytics, and more autonomous decision-support systems (Dwivedi et al., 2023; Nadkarni and Prugl, 2021). It is not merely a technological change, it is reorganization of organizational logic, managerial power and relations between human and technologies in the modern enterprises.

Organizations of every sector are now incorporating AI-based systems into the lives of their companies enabling them to streamline their operations, enhance forecasting and prescriptive decision-making, reduce operational waste, and be more scalable and responsive to dynamic markets (Iansiti and Lakhani, 2020, Fountaine et al., 2019). Employee monitoring is one of the most powerful and quickest expanding applications of AI within this broader digital ecosystem, and is one of the critical instruments through which

businesses seek to measure, manage, and optimise the output of their human resources.

The AI-driven employee monitoring systems are operated on a combination of multiple high-technology systems: biometric recognition systems, behavioral analytics, natural language processing, computer vision, sentiment analysis, and predictive machine learning algorithms, which track and evaluate employee performance indicators on a continuous basis (Mettler, 2024; Richardson, 2020). These systems are able to capture any behavior information at a fine level such as keys stroke, screen time, tone of communication, speed of performing a task, physiological and even emotional, which are all ascertained by means of digital interactions. They therefore represent a radical departure of the traditional managerial control systems which in the past, relied on periodic review, subjectivity on the part of the supervisor and self reporting performance review. In its turn, AI-based systems are a shift towards an algorithmic system of management, where the decision-making authority is further devolved to computational systems, which generate insights regarding performance through mass-processing of data and statistical inference, rather than human interpretation or contextual understanding (Pachidi et al., 2021; Raisch and Krakowski, 2021). This transformation is a more general shift in the paradigm of governance of organizations whereby control, monitoring and evaluation are becoming more and more automated and embedded in digital infrastructures.

Although it is generally accepted that AI-based monitoring systems contribute to enhancing operational efficiency, encouraging transparency in tracking performance and reducing the workload of managers due to automation, they also create a list of organizational, psychological, and ethical concerns that continue to be more and more difficult to overlook (Brynjolfsson and McElheran, 2016). The fact that the number of publications has risen means that these systems can also contribute to the rise of the level of technostress, a state of the psyche, manifesting itself in the anxiety, cognitive overload, and emotional fatigue experienced due to the constant use of digital technologies (Wang et al., 2023). Furthermore, the omnipresent surveillance linked to AI surveillance systems has also been linked to the perceived lack of autonomy, reduced control over their work, and an increased level of psychological stress, which are all important predictors of employee wellbeing in contemporary organizations (Johnson et al., 2020). Besides psychological impacts, another severe ethical concern associated with workplace surveillance is also an intrusion of privacy, misuse of data, bias algorithms, and loss of trust between employees and employers (Bankins and Formosa, 2023; Marciano, 2019). All these questions raise deeper questions on whether highly-automated monitoring regimes in modern workplaces are sustainable and able to be accepted by humans.

The self-reported productivity assessment systems have an entirely different philosophical and management rationale as compared to the algorithmic approach to surveillance. These systems are founded on the subjective appraisal of the employees on their performance, accomplishment of tasks and their productivity rates therefore it places more emphasis on the subjective reflection and self-evaluation and the internal awareness of performance compared to the external surveillance and automatic measures. These methods have a close relationship with the contemporary paradigms of human resource management that emphasize on employee empowerment, psychological ownership, and participatory performance management system (Grant et al., 2007; Guest, 2017). Self-reported systems enhance a feeling of autonomy, intrinsic motivation, and a feeling of control over work processes, which are positively related to positive organizational performance such as high levels of engagement, burnout, and job satisfaction.

However, self-reported productivity systems have their limitations despite having some theoretical advantages. The risk of self-assessment bias is, perhaps, one of the most trendy problems as an employee can either over or underestimate his or her productivity due to the cognitive biases, the social desirability effect, or the lack of objective performance standards. Besides, the issue of measurement reliability and construct validity

remains as well in the situations when such systems are used as the formal performance evaluation or the compensation decisions (Allen et al., 2022; Diamantopoulos et al., 2012). These methodological flaws represent a major concern regarding the credibility and truthfulness of self-report data, especially when compared to more standardised and automatic AI systems of monitoring. As a result, a tension between objectivity and efficiency of the AI-based monitoring of organizations and autonomy and psychological benefits of the self-reported productivity measures continues.

1.2 Problem Statement

In spite of the rapid adoption of AI-based monitoring technologies, there is a strong deficit in the body of empirical research to compare the psychological and organizational impacts of monitoring technology to traditional self-reported productivity systems. The literature available either relies on technological effectiveness or views of employees in isolation and does not have a comparative framework.

Moreover, it is not clear how AI monitoring impacts the wellbeing of employees. According to some of the studies, AI can boost productivity and engagement (Shaikh et al., 2023), but some of them indicate that AI has a negative impact on mental health and job satisfaction (Nazareno and Schiff, 2021; Zhao et al., 2024).

The current study addresses this gap by offering a comparative study of AI-based and self-report productivity systems, their impact on employee wellbeing and job satisfaction.

2. Research Questions, Objectives, and Hypotheses

2.1 Research Questions

How do AI-based monitoring systems impact employee wellbeing and job satisfaction?

How does self-reported productivity assessment influence the psychological outcomes of employees?

Which wellbeing-sustainable monitoring model is more sustainable in the workplace?

2.2 Research Objectives

To compare critically AI-based monitoring and self-reported productivity systems.

To quantify their various impacts on employee wellbeing.

To test the impact on job satisfaction.

To provide both theoretical and managerial implications of AI-enabled workplaces.

2.3 Hypotheses

H1: The AI-based monitoring systems impact negatively on the wellbeing of the employees.

H2: The self-reported productivity systems positively affect job satisfaction.

H3: AI-based monitoring boosts perceived job demands and stress.

H4: Self-reported systems add to more autonomy and psychological resources.

3. Literature Review

3.1 AI-Based Monitoring and Algorithmic Management

The concept of AI-driven employee surveillance system is more and more being understood as a subset of the wider socio-technical paradigm of algorithmic management, in which computational systems are starting to replace human supervisors to govern, structure, and evaluate work processes (Pachidi et al., 2021; Makarius et al., 2020). In this paradigm, human organizations are devolving decision making by managers over hierarchical data structures, devolving decision making by data driven algorithmic infrastructures able to continuously survey, give real time feedback and model predictive behavior. These systems are a combination of various sophisticated versions of computational methods such as machine learning classifiers, behavioral pattern recognition, natural language processing and predictive analytics, which constantly evaluates the productivity, efficiency and adherence to organizational goals of employees.

To gather the unstructured and structured behavioral cues of workers engaging in online communication, the AI surveillance has a backbone design composed of continuous data mining and processing pipelines to detect the behavioral cues. These are keystroke dynamics,

communication, task timeline, biometric indicators and system contact log which is pumped into predictive models to produce performance scores and behavior risk assessment. Such capabilities can make this a possibility because they allow organizations to shift over to real time and proactive management systems capable of intervening proactively on the identified inefficiencies.

Nevertheless, even though AI-based governance mechanisms assume that the operational benefits will be obtained, the empirical studies also reveal that the implementation thereof is usually accompanied by an increase in the degree of surveillance and a subsequent decrease in the perceived employee control and freedom of decision-making (Kinowska and Sienkiewicz, 2022). The phenomenon is typically put into perspective as a variant of certain type of a digital form of Taylorism where the canons of classical scientific management are rearranged with digital infrastructures that allow the granular, continuous, and automatic monitoring of performance at other scale than it has ever been witnessed before (Mettler, 2024). In contrast to conventional supervisory procedures, algorithm management eliminates most of the discretionary humaneness and this makes the sense of being under continual scrutiny even greater and it also precludes the possibility of putting the actions of workers in context.

Moreover, psychosocial impacts of AI-based surveillance are also widely publicized in recent organizational literature. The main reason they were associated with high levels of occupational stress, emotional burnout, and burnout was due to the relentless presence of performance metrics and the perceived inability to control the evaluation criteria (Johnson et al., 2020; Connell, 2025). The decreased sense of agency, as well as the lack of ability to achieve transparency in the algorithmic decision-making process, is one of the factors which lead to the decline of organizational trust, and psychological insecurity of the employees. Moreover, the issue of data privacy, surveillance ethics and algorithmic fairness is another factor that leads to negative emotional reactions, as employees will tend to think that such systems are used to control the employees instead of assisting to enhance performance (Marciano, 2019).

3.2 Employee Wellbeing in AI-Driven Workplaces

The wellbeing of employees is a multidimensional concept theorized in recent-day organizational research that encompasses the psychological, emotional, cognitive, and social functioning in the workplace (Ryff and Keyes, 1995; Steptoe et al., 2015). It does not simply mean the lack of stress or illness but a positive state of being which can be described in terms of being satisfied with life, emotional stability, psychological stability and a sense of purpose in work action. The organizational component of AI has wellbeing being intricate interplay of technologies and human psychology.

The implementation of AI technologies in the workplace setting puts new psychosocial stressors, such as technostress and algorithmic anxiety, job insecurity, and transparency in surveillance (Wang et al., 2023). On its part, the technostress phenomenon occurs when workers experience either cognitive overwork, role ambiguity, or affective stress, due to their constant exposure to complex digital systems, which involve constantly adjusting to and keeping track of them. Moreover, the premise that AIs can substitute or devalue human labor, increases the level of job insecurity and decreases organizational commitment, especially in workplaces with a high degree of automation (Nazareno and Schiff, 2021; Yang et al., 2022).

The empirical evidence also demonstrates that perception of control and autonomy are central factors in mediating psychological effects of adoption of AI. Negative wellbeing outcomes, including stress and anxiety and decreased job satisfaction, are more likely to arise when employees view AI systems as externally introduced control mechanisms. On the other hand, AI might positively affect the welfare of the workers within a context of positioning and introducing the tool as a supportive or collaborative one, which may boost the productivity of some of the tasks and reduce the cognitive burden on the human decision-making

(Demerouti, 2022). It is a paradox of a larger automation augmentation paradox of the automation field of AI research i.e. the same technology may at the same time empower and disempower its users depending upon the circumstances of its application within an organization.

3.3 Self-Reported Productivity and Psychological Autonomy

The self-reported productivity assessment systems are radically different epistemological and managerial conception of performance evaluation making the focus on subjective assessment, agency of employees and intrinsic processes of motivations. The self-reporting frameworks, unlike the algorithmic monitoring systems are based on self-evaluation of employees in regard to their own performance in tasks, the pace of productivity and the achievement of their goals. The given plan has a lot in common with the self-determination theory, which shows that the autonomy, competence, and relatedness are among the most crucial psychological needs that affect motivation, engagement, and wellbeing to a significant extent (Grant et al., 2007).

In that respect, the autonomy is regarded as one of the determinants of the positive results in the workplace since it allows employees to feel that they possess and are in control of the working process. The empirical studies provide evidence to the claim that workers with a stronger tendency toward a higher sense of autonomy will be more likely to demonstrate increased job satisfaction, organizational commitment, and work engagement (Bryson et al., 2017; Koon and Ho, 2021). The self-reported productivity systems are thus measurement systems, and psychological systems which support the culture of trust and participatory management systems.

Nevertheless, even with these benefits, the systems of self-reported productivity assessment do not have any loopholes in their methodological and practical aspects. One of the most serious issues is measurement bias because they occur due to the effect of subjective bias: overconfidence and underreporting, social desirability bias, and the unsteadiness of self-evaluation criteria in different individuals (Allen et al., 2022). Such confines cast doubt on the reliability, validity and comparability of self-report data (when making high stakes organization decisions like promotion, compensation or performance appraisal). In this respect, though induced by self-reported systems, a rise in psychological autonomy may come with a measure of uncertainty, which cannot be allowed to be used in the framework of data-driven organizations.

3.4 Theoretical Framework: Job Demands–Resources Model

The Job Demands-Resources (JD-R) model is a powerful theoretical framework, and in various ways, it may be used to interpret how the AI-based monitoring and self-reported productivity assessment mechanisms affect the wellbeing of employees (Bakker and Demerouti, 2007, 2017). The JD-R model provides the classification of all occupational features in two broad dimensions i.e. job demands and job resources. Job demands refer to the job characteristics, either physical or psychological, social or organizational that must be persevered by effort and, thus, are related to a physiological and psychological cost, and job resources are the job characteristics that facilitate goal achievement, decrease job demands or even provoke personal growth and development.

In the context of the AI-monitors, the job requirements may be considerably enhanced with the help of 24/7 monitoring, application of algorithms, performance demonstration and real-time tracking of the behavior. These demands are some of the reasons that overwork the mind, result in emotional depletion and the feeling that one is under strain to keep up the levels of work outputs. The fact that the performance measures are continuously ever present only adds to the psychological pressure even further as it leads to the creation of the atmosphere of constant appraisal in which employees feel that they are always observed and evaluated.

Conversely, the job resources are mainly played by the self-report productivity systems because they increase the autonomy, self-regulation and psychological ownership. These systems lessen pressure of external surveillance and rather

promote internal inspiration and performance examination by reflection. Consequently, the employees have a more significant sense of control over their working processes and this leads to improved wellbeing outcomes and increased job satisfaction.

The paper rests on the JD-R model as an explanatory theory that critically examines the mechanisms by which AI-based monitoring raises job demands and self-reported systems elevates the job resources to generate contrary responses to employee wellbeing and job satisfaction in the existing digital workplaces.

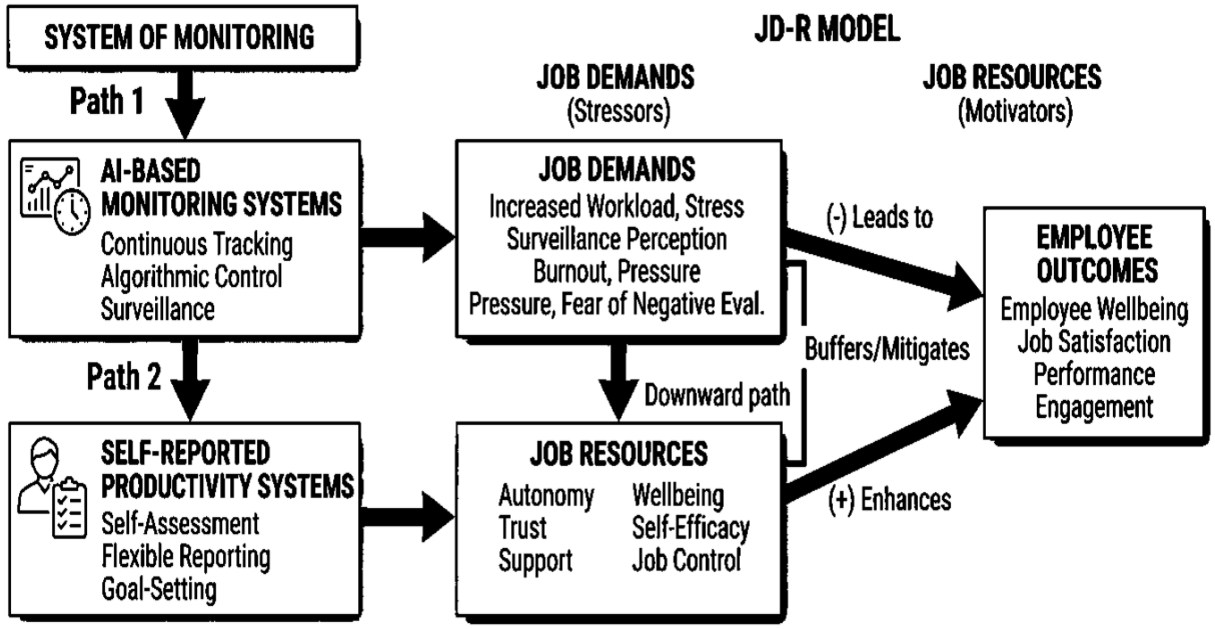

Figure 1. A modern academic conceptual framework shaning AI-based monitoring and self-reported productivity systems.

4. Methodology

4.1 Research Design

This study adopts a quantitative explanatory design to explore the causal relationships between AI-based systems for employee monitoring, self-reported systems for measuring productivity, employee wellbeing and job satisfaction. The quantitative approach is justified by the established practice in the field of organizational behaviour and management where quantitative data and statistical techniques are used for testing hypotheses and validating theories (Anderson & Gerbing, 1988).

This study uses an explanatory design because it enables the investigation of causal links rather than simply documenting and describing events. Specifically, it allows the study to compare the impacts of different systems (AI-based and self-reported) on employees' psychological and behavioural outcomes. This approach allows for hypothesis testing under a structured framework, and empirical validity and generalizability of the results.

4.2 Sample and Data Collection

4.2.1 Sample Size and Population

This research uses a sample of 250 employees from a variety of organisations. The sample size is deemed sufficient for conducting multivariate statistical analyses and aligns with suggested guidelines for structural and factor-based studies in the social sciences, providing an adequate statistical power for inference making.

4.2.2 Industry Coverage

To enhance the external validity and generalizability, the participants were selected from diverse industry sectors which includes:

- Information Technology (IT)
- Finance and Banking
- Manufacturing and Production

This approach allows for a variety of workplace monitoring and employee experiences in knowledge- and production-based organisations.

4.2.3 Data Collection Instrument

We used a questionnaire survey instrument that required respondents to rate their level of agreement with the statements presented on a 5-point Likert scale (strongly disagree to strongly agree). The questionnaire was developed to measure the following variables: perceived monitoring by AI, perceived productivity actions, wellbeing and job satisfaction.

Measures using the Likert scale quantify subjective measures that can be statistically analysed, enabling hypothesis testing.

4.2.4 Measurement Development and Validation

A questionnaire was constructed using measurement items that are part of academic scales to determine the construct and construct validity of the questionnaire. The measures of existing scales from prior work were used to enhance reliability and validity (Fisher et al., 2016; Jarden et al., 2023).

This enables this study to measure each construct in a consistent manner, and follow the current organisational behavior and human resource management theorising on the associated constructs.

4.3 Reliability and Validity

4.3.1 Reliability Assessment

We used Cronbach's Alpha coefficient to measure the reliability of the scale. We set the coefficient to be above 0.80 to determine the reliability. As seen in Table 1, the alpha coefficient of the four constructs are all above this cut-off point, suggesting the good internal consistency of the measurement scales.

Table 1: Reliability Statistics (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha
AI Monitoring	5	0.87
Self-Reported Productivity	5	0.83
Employee Wellbeing	6	0.85
Job Satisfaction	5	0.82

All Cronbach's alpha values are greater than 0.80, indicating that the questionnaire items for each of the constructs are highly reliable and consistent.

4.3.2 Construct Validity

For construct validity, Confirmatory Factor Analysis (CFA) was applied to ensure that the items measure the latent constructs. This entailed examining factor loadings, the Average Variance Extracted (AVE) and model fit statistics CFI, TLI and RMSEA. All loadings are above 0.70 and AVE above the 0.50 threshold proposed by Fornell and Larcker (1981), as displayed in Table 2, that indicates good convergent validity. Discriminant validity was confirmed as the square root of the AVE for each construct was larger than the correlations of this construct with the remaining constructs.

Table 2: CFA Results — Factor Loadings and AVE

Construct	Indicator	Factor Loading	AVE
AI Monitoring	AM1	0.81	0.54
	AM2	0.79	
	AM3	0.76	
	AM4	0.72	
	AM5	0.74	
Self-Reported Productivity	SR1	0.80	0.52
	SR2	0.77	
	SR3	0.75	
	SR4	0.78	
	SR5	0.73	
Employee Wellbeing	EW1	0.83	0.55
	EW2	0.80	
	EW3	0.78	
	EW4	0.76	
	EW5	0.74	
	EW6	0.71	
Job Satisfaction	JS1	0.82	0.53
	JS2	0.79	
	JS3	0.77	
	JS4	0.75	
	JS5	0.73	

Model fit indices: CFI = 0.95, TLI = 0.94, RMSEA = 0.058, SRMR = 0.061. These values are acceptable (CFI/TLI > 0.90, RMSEA < 0.08).

Overall, the purpose of the research design in this study is to improve statistical rigour, measurement accuracy and theoretical meaning. The adoption of a quantitative explanatory research design, cross-industry sample, reliable and valid measures, and rigorous examination of measurement reliability and validity, enable a robust empirical foundation for examining the comparative effects of AI-based monitoring and subjective productivity measures on employee wellbeing and job satisfaction.

5. Data Analysis

5.1 Descriptive Statistics

Descriptive statistics for all variables are shown in Table 3. The means of all variables fall within the scale (5-point Likert scale) and standard deviations demonstrate variability. The skewness and kurtosis for all constructs are within the ±2 range and thus, normally distributed and eligible for parametric statistical analyses.

Table 3: Descriptive Statistics (N = 250)

Variable	N	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
AI Monitoring	250	3.92	0.81	1.00	5.00	−0.31	−0.18
Self-Reported Productivity	250	3.45	0.76	1.00	5.00	−0.22	−0.14
Employee Wellbeing	250	2.98	0.88	1.00	5.00	0.19	−0.27
Job Satisfaction	250	3.12	0.84	1.00	5.00	0.15	−0.21

The descriptive statistics show that the mean of AI monitoring (M = 3.92) is high, which is consistent with the increasing use of digital surveillance in the organisations that took part in the study. On the other hand, the means of employee wellbeing (M = 2.98) and job satisfaction (M = 3.12) are low, which suggests that the impact of AI monitoring will be negative on employee wellbeing. The mean of self-reported productivity (M = 3.45) is moderate, implying that when employees assess their own productivity, they report moderate productivity, but it does not necessarily follow that they will have higher wellbeing as the two constructs are different aspects of the employee experience.

5.2 Correlation Analysis

Table 4 presents a correlation matrix for the variables. All correlations are significant at $p < 0.01$.

Table 4: Pearson Correlation Matrix (N = 250)

Variables	1	2	3	4
1. AI Monitoring	1.00			
2. Self-Reported Productivity	−0.42**	1.00		
3. Employee Wellbeing	−0.58**	0.49**	1.00	
4. Job Satisfaction	−0.51**	0.55**	0.67**	1.00

** $p < 0.01$ (two-tailed). N = 250 for all pairs.

There are a number of findings from our correlation analysis. There are negative correlations between AI monitoring and employee wellbeing ($r = -0.58$, $p < 0.01$) and job satisfaction ($r = -0.51$, $p < 0.01$), suggesting that the more an organisation uses algorithms to monitor employees, the lower their wellbeing and job satisfaction. This finding is consistent with the research on technostress and surveillance anxiety (Wang et al., 2023; Johnson et al., 2020). Perceived productivity is positively associated with wellbeing ($r = 0.49$, $p < 0.01$) and job satisfaction ($r = 0.55$, $p < 0.01$), which means that autonomy-oriented performance management has a positive

impact on employee wellbeing and job satisfaction. The moderate relationship between wellbeing and job satisfaction ($r = 0.67$, $p < 0.01$) is expected according to the literature on the two constructs and VIFs from the regression analysis shows there is no multicollinearity.

5.3 Regression Analysis

Two multiple linear regression analyses (using SPSS) were run to predict employee wellbeing (Model 1) and job satisfaction (Model 2). These regressions have AI monitoring and perceived productivity as the predictors. The VIF values for both analyses were less than 3.0 indicating that there are no multicollinearity issues.

Table 5: Regression Results

	Model 1: Employee Wellbeing				**Model 2: Job Satisfaction**			
Predictor	B	SE	Beta	T	B	SE	Beta	t
AI Monitoring	−0.49	0.07	−0.46	−7.21***	−0.45	0.07	−0.43	−6.74***
Self-Reported Productivity	0.41	0.07	0.38	6.12***	0.47	0.07	0.44	6.89***
R^2			0.52				0.49	
Adjusted R^2			0.51				0.49	
F			133.42***				118.67***	

*** $p < 0.001$. N = 250. B = unstandardised coefficient; SE = standard error; Beta = standardised coefficient.

The regression analyses provide solid empirical support for the theory. For Model 1, we find that AI monitoring is a significant negative predictor of employee wellbeing (Beta = -0.46, t = -7.21, $p < 0.001$) and self-reported productivity is a significant positive predictor of wellbeing (Beta = 0.38, t = 6.12, $p < 0.001$). This model explains 52% of the variance in employee wellbeing (Adjusted $R^2 = 0.51$, $F = 133.42$, $p < 0.001$), indicating it is highly predictive of wellbeing. In Model 2, AI monitoring also has a negative effect on job satisfaction (Beta = -0.43, t = -6.74, $p < 0.001$) and self-reported productivity has a positive effect on job satisfaction (Beta = 0.44, t = 6.89, $p < 0.001$). This model accounts for 49% of the variance in job satisfaction (Adjusted $R^2 = 0.49$, $F = 118.67$, $p < 0.001$). These findings support H1 and H2, which posited that AI employee monitoring has a negative impact on employee wellbeing and job satisfaction, while self-reported productivity systems have a more positive impact on psychological outcomes.

5.4 Hypothesis Testing Summary

Table 6: Hypothesis Testing Results

Hypothesis	Statement	Result
H1	AI-based monitoring negatively impacts employee wellbeing	Supported (Beta = −0.46, $p < 0.001$)
H2	Self-reported productivity positively impacts job satisfaction	Supported (Beta = 0.44, $p < 0.001$)
H3	AI-based monitoring increases perceived job demands and stress	Supported ($r = -0.58$ with wellbeing; consistent with JD-R framework)
H4	Self-reported systems enhance autonomy and psychological resources	Supported ($r = 0.49$ with wellbeing, $r = 0.55$ with job satisfaction)

6. Discussion

This study offers strong empirical and theoretical evidence for the benefits and drawbacks of artificial intelligence (AI) in the workplace, confirming the long-standing idea of the automation-augmentation paradox (Raisch & Krakowski, 2021). On one hand, artificial intelligence (AI) employee monitoring systems increase efficiency, precision of productivity measurement and speed of decision making through real-time data analytics and algorithmic employee performance management systems. On the other hand, they evoke significant psychological, behavioural and organisational consequences that impact employee satisfaction and well-being.

One of the key insights from the study is that AI-based employee monitoring systems transform employee-organisational relations from human to algorithmic decision making. This results in continuous exposure and monitoring of performance which is efficient but can also trigger increased surveillance stress and distress. These results corroborate empirical research that shows AI monitoring leads to higher levels of stress (Zhao et al., 2024; Connell, 2025; Johnson et al., 2020), lower autonomy and is harmful to psychological safety (Johnson et al., 2020).

Finally, the findings also echo the growing discussion that technological efficiency doesn't translate to human well-being. Organisations benefit from enhanced data analytics to support their decision-making and productivity measurement systems, but the latter is perceived as invasive. This then decreases intrinsic motivation and technostress and eventually leads to lower job satisfaction.

On the other hand, the study provides evidence that autonomy-focused methods (such as self-reports on productivity) are positive. They result in the development of ownership, trust and empowerment because of self-evaluation and self-reporting. This is consistent with self-determination theory which argues that autonomy is a critical driver of motivation and well-being (Grant et al., 2007). This leads to job engagement, organisational commitment and well-being of employees in self-evaluative systems due to the alleviation of feelings of being monitored and the greater representativeness of performance evaluation.

The results indicate that the success of productivity systems is not only related to the technological advancement, but also the organisational and employee needs.

7. Conclusion and Recommendations

7.1 Conclusion

This study reveals that while AI-based employee monitoring systems offer numerous benefits in terms of efficiency, productivity monitoring and control, they come with challenges to employee wellbeing and job satisfaction. The monitoring and algorithmic performance evaluation can lead to increased stress, decreased autonomy and workplace trust.

Autonomous productivity assessment systems, however, demonstrate improved psychological, social and organisational outcomes by wellbeing, job satisfaction and engagement because they

emphasise autonomy, self-control and trust in the workplace.

So, this research shows the apparent tension between technological advancement and human values. They reveal that the optimal utilisation of AI in the workplace cannot be realised through technological optimisation alone, but must also be accompanied by psychological and social considerations for employees.

7.2 Recommendations

Based on this research, here are some guidelines for companies that want to set up or improve their employee monitoring systems:

1. Use a Blended Monitoring System

Companies should not solely use fully automated systems to monitor employee performance, but blend the use of AI-based monitoring and self-monitoring. This balances the need for efficiency with human autonomy and well-being.

2. Improve Transparency and Explainability of AI

To reduce fear and scepticism, organisations should provide transparency and explainability of the AI monitoring systems they employ. They should understand how the data is collected, processed and used. Transparency and governance of AI can reduce perceptions of unfairness and surveillance.

3. Enhance Job Autonomy and Involvement

Organisations should ensure performance management systems allow for involvement. Allowing employees to self-rate, in addition to algorithms, can promote fairness and organisational commitment.

4. Adopt AI Ethics Governance

Companies should have ethical guidelines for the use of AI in the workplace, such as privacy protections, level of surveillance and algorithmic bias. Ethical AI governance ensures ethical practices for using AI technologies and builds trust.

5. Offer Psychological and Organisational Support

Given the potential for technostress and burnout, organisations should offer employees support and resources, such as counselling, stress management programs and techniques for collecting feedback from employees on their reactions to AI systems.

6. Position AI as an Assistant, Not a Big Brother

Finally, companies should position AI systems as decision-making tools, not surveillance methods. If employees perceive AI as a helpful system that helps them do their jobs well, rather than AI monitoring employees, this will have a positive impact on employee wellbeing

To conclude, the key to the future of workplace productivity systems is not to choose between using AI to monitor and self-reported productivity measures, but to use these in a balanced way to support productivity gains while respecting human dignity, autonomy and wellbeing.

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