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EFFECTS OF USING INTERNET OF THINGS (IoT) FOR EMPLOYEE WELL-BEING AT THE WORKPLACE

An Empirical Investigation of Smart Workplace Technologies, Privacy Concerns, and Employee Well-Being

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Abstract — Purpose — The Internet of Things (IoT) is becoming more and more a part of the organisational world with smart desks, wearable sensors, environment responsive lighting/HVAC systems and workplace analytics platforms. Such systems are sold as a way to make employees more comfortable, more aware of their health and more productive, but they also create issues of surveillance and data privacy that can outweigh the benefits. This study investigates the impact of IoT adoption, IoT workplace comfort, IoT health and stress monitoring, privacy/surveillance concern and IoT work-life balance on employee well-being through an empirical study.

Design/methodology/approach — The design used was quantitative, cross sectional survey. Data were gathered (n = 220) with a 24-item, five-point Likert scale questionnaire that measured six constructs. Descriptive statistics, Cronbach's alpha, Kaiser-Meyer-Olkin (KMO) and Bartlett's test, Pearson correlation, multiple linear regression, independent-samples t-test, one-way ANOVA with Tukey post-hoc tests and chi-square analysis were used to analyse the data.

Findings — Workplace comfort, health/stress monitoring, and work-life balance were significant positive predictors of employee well-being, and privacy/surveillance concern was a significant negative predictor of employee well-being, even though it was only weakly positively correlated with employee well-being (a suppression effect). About 50% of the variance in employee well-being was accounted for by the regression model.

Originality/value — The study provides an integrated, empirically testable model that captures both the functional benefits and the surveillance costs of workplace IoT, and that can help clarify the previously fragmented literature and guide the responsible design of IoT-enabled workplace systems.

Keywords — *Internet of Things; Employee Well-Being; Smart Workplace; Wearable Technology; Privacy Concerns; Workplace Surveillance; Multiple Regression*

I. Introduction

Internet of Things (IoT) technologies are being quickly adopted by organisations in manufacturing, corporate and knowledge-work environments to sense, monitor and react to the physical and physiological state of their workforce. These technologies include ambient sensors that automatically adjust lighting, temperature, and air quality (Aryal, Becerik-Gerber, Anselmo, Roll, & Lucas, 2019; Barišić, Amaral, & Challenger, 2020) as well as wearable devices that continuously monitor heart rate, movement, and stress indicators (Al-Atawi et al., 2023; Jacobs et al., 2019). Vendors and early adopters position these systems as a path to healthier, more comfortable, and more productive workplaces (Gatea, Al-Ibadi, & Ali, 2024; Sun, Zheng, Gong, Paredes, & Ordieres-Meré, 2020). Meanwhile, a parallel and growing body of research shows that constant IoT monitoring can be felt by workers as surveillance, which can lead to a loss of trust, autonomy, and ultimately well-being (Kalischko & Riedl, 2021; Glavin, Bierman, & Schieman, 2024). This tension is not merely theoretical. Gómez-Carmona, Casado-Mansilla, López-de-Ipiña and García-Zubía (2024) discovered that workers who participated in wellness e-health programmes in their workplace expressed significant concerns regarding the collection, storage and use of their personal data. Gupta, Lakhera, Joshi, Sharma and Shah (2024) also suggest that IoT devices can be considered as a new source of 'digital stress' because of the constant flow of digital demands and monitoring cues from the environment.

Although these conflicting results exist, the majority of the literature focuses on the functional aspects of IoT (comfort, health monitoring, ergonomics) and the surveillance aspects (privacy concern, electronic monitoring) as two distinct research streams, and few studies model both together to a single well-being outcome. The present study aims to fill this gap by testing an integrated model where IoT adoption/usage, IoT-enabled workplace comfort, IoT-based health and stress monitoring, and IoT-supported work-life balance are expected to positively predict employee well-being, and privacy/surveillance concern is expected to negatively predict employee well-being. This study is able to estimate all five effects at once in a single multiple regression model, which allows for the isolation of the unique contribution of each mechanism, including any suppression effects that would not be apparent in bivariate analysis alone. The rest of this paper reviews the literature, presents the conceptual framework and hypotheses, outlines the methodology of the survey, presents descriptive and inferential results, and discusses the theoretical and practical implications of the results.

II. Literature Review

2.1 IoT in the Workplace: Concept and Scope

The Internet of Things (IoT) in the workplace is a network of sensors, actuators, wearables and connected devices that are embedded in the built environment and on the employees themselves, producing a continuous stream of data to optimise the working environment (Nappi & Ribeiro, 2020). As early as 2015, Russo termed this trend the rise of the 'quantified workplace', where management is more and more turning to metrics derived from sensors to gain insight into how work is actually being done. Gatea et al. (2024) surveyed the current state of smart-office systems and found that there are three common functional layers: environmental control (lighting, HVAC, occupancy), asset and space management, and occupant-health monitoring. This is further discussed by Paoloni, Massaro, Mas and Lombardi (2023), who explicitly connect the deployment of IoT to the wider agenda of human sustainability, and thus consider that the adoption of technology in organisations should be assessed not only for efficiency gains but also for its overall impact on the humans who operate within it, a perspective that this study embraces.

2.2 IoT, Workplace Comfort, and Productivity

A substantial stream of research links IoT-enabled environmental control to employee comfort and, indirectly, to productivity. Aryal et al. (2019) proposed 'smart desks' instrumented with posture and environmental sensors as a mechanism to promote comfort and health in offices, arguing that continuous micro-adjustment of the workspace reduces physical strain across the workday. Barišić et al. (2020) reported that smart-office configurations that let systems automatically respond to occupant needs increased both self-reported comfort and subjective well-being. Valk, Myers, Atkinson, and Mohring (2015) used sensor networks to correlate ambient comfort conditions with productivity outcomes, finding a measurable relationship between environmental quality and work output. Vildjiounaite et al. (2020) similarly demonstrated, using an 'internet of office desks' platform, that sensor-informed nudges toward better posture and desk configuration were positively received by employees. However, Kożusznik et al. (2019), in a systematic review, cautioned that energy-efficiency-oriented smart-office deployments do not automatically translate into well-being gains unless comfort and efficiency objectives are explicitly decoupled and separately optimised for the occupant. Sun et al. (2020) proposed a Human Cyber-Physical System architecture ('Healthy Operator 4.0') that integrates physiological, environmental, and productivity sensing into a single feedback loop explicitly designed around operator health.

2.3 Wearables, Health, and Stress Monitoring

A second major stream examines wearable IoT devices used specifically for health and stress monitoring. Al-Atawi et al. (2023) developed a machine-learning pipeline that combines wearable sensor data with IoT infrastructure to detect elevated stress in near real time, demonstrating the technical feasibility of continuous workplace stress surveillance. Hijry et al. (2024) extended this logic to industrial settings, building a real-time worker-stress prediction system for a smart factory assembly line. Naranjo, Mora, Villagómez, Falconi, and García (2025) reviewed wearable sensors in industrial ergonomics and concluded that such devices meaningfully enhance both safety and productivity when properly integrated into Industry 4.0 workflows. Nataraj, Prabha, S, Jeynth, and Winters (2025) proposed an AI-enhanced wearable specifically for remote stress management, while Stepy et al. (2026) combined wearable and social-media signal data in a hybrid AIoT model to predict and intervene on workplace stress. Jacobs et al. (2019) provide an important counterpoint from the employee-acceptance perspective, showing that adoption and sustained use of workplace wearables depends heavily on perceived usefulness, trust in the organisation, and perceived control over one's own data — a finding echoed by Mettler and Wulf (2018), who described the affordances and constraints of 'physiolytics' (self-tracking technology) from the employee's own point of view, and Chung, Gorm, Shklovski, and Munson (2017), who found that employees actively negotiate and personalise how self-tracking data is shared with employers to 'find the right fit' between usefulness and intrusion.

2.4 Privacy, Surveillance, and the Well-Being Trade-off

A distinct and increasingly influential stream of literature interrogates the well-being costs of the same monitoring infrastructure. Kalischko and Riedl (2021) conducted a comprehensive review of electronic performance monitoring in the digital workplace and concluded that, although monitoring can improve managerial oversight and, in some conditions, performance, its effects on employee psychological well-being are frequently negative, moderated by factors such as perceived fairness and transparency of the monitoring system. Glavin, Bierman, and Schieman (2024) empirically linked workplace surveillance intensity to reduced worker well-being using large-scale survey data, framing pervasive monitoring as a chronic low-grade stressor. Gómez-Carmona et al. (2024) focused specifically on IoT-based workplace wellness e-health programmes and found that employees' perceptions of privacy and data control were a decisive factor in whether such programmes were experienced as supportive or intrusive. Gupta et al. (2024) argued that the proliferation of IoT devices itself — independent of any single monitoring policy — constitutes an emerging threat to employee well-being through the mechanism of digital stress. Together, this literature suggests that the same sensing infrastructure that enables comfort and health benefits can simultaneously function as a source of surveillance-related strain, motivating the inclusion of privacy/surveillance concern as a distinct, negatively signed predictor in the present study's model.

2.5 IoT, Remote/Smart Environments, and Broader Well-Being Outcomes

Beyond the traditional office, Marikyan, Papagiannidis, Rana, and Ranjan (2023) examined smart-home environments used for remote work and found that smart-home technology positively influenced productivity, well-being, and future use intention, while also identifying perceived risk as a countervailing factor — a structural parallel to the comfort/privacy trade-off examined in the present study. Ahmad and Zulkifli (2022) took a broader view, arguing conceptually that IoT can be positioned as part of the 'road to happiness' when designed around human needs rather than purely operational metrics. Fleming (2020) reviewed workplace wellness programmes in the era of pervasive technology and big data, cautioning that the effectiveness of technology-enabled wellness initiatives depends on organisational trust and governance as much as on the technology itself. Collectively, the reviewed literature converges on two consistent themes that directly motivate the present study's hypotheses: (a) IoT-enabled comfort, health monitoring, and work-life support mechanisms are generally associated with improved employee outcomes, and (b) privacy and surveillance concerns represent a distinct, negatively-signed pathway that can offset these benefits and must be modelled explicitly rather than assumed away.

III. Conceptual Framework and Hypotheses

Drawing on the reviewed literature, this study proposes an integrated model in which four IoT-related mechanisms — usage/adoption, workplace comfort, health and stress monitoring, and work-life balance support — are hypothesised to positively influence employee well-being, while a fifth mechanism, privacy/surveillance concern, is hypothesised to negatively influence it. The five constructs are modelled as simultaneous, independent predictors of a single outcome variable, allowing their unique (partial) effects to be estimated net of one another.

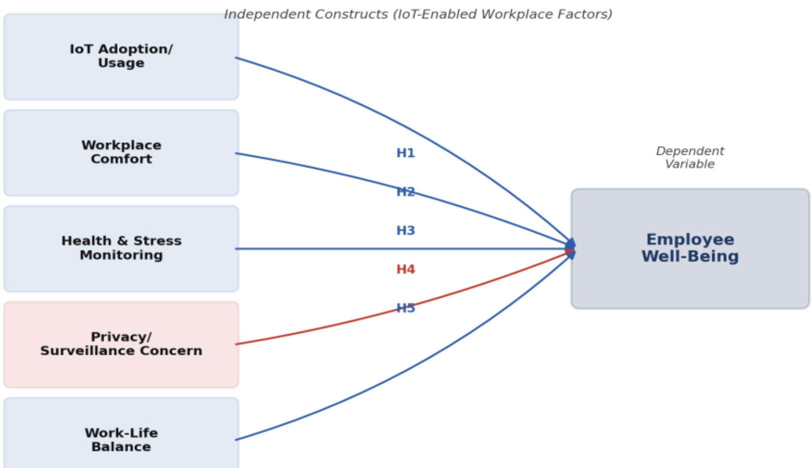


Figure 1. Conceptual research framework linking IoT-related workplace constructs to employee well-being.

Table 1. Research hypotheses

Hypothesis	Statement
H1	IoT adoption/usage has a significant positive effect on employee well-being.
H2	IoT-enabled workplace comfort has a significant positive effect on employee well-being.
H3	IoT-based health and stress monitoring has a significant positive effect on employee well-being.
H4	Privacy/surveillance concern arising from IoT use has a significant negative effect on employee well-being.
H5	IoT-supported work-life balance has a significant positive effect on employee well-being.

IV. Methodology

4.1 Research Design and Sample

A quantitative, cross-sectional survey design was adopted to test the hypothesised relationships. The target population comprised employees working in organisations that have deployed one or more forms of workplace IoT technology (smart environmental controls, wearable devices, or workplace analytics platforms). A structured questionnaire was used for data collection, and responses were analysed using IBM-compatible statistical routines implemented in Python (SciPy, statsmodels, factor_analyzer). The analysed sample comprised 220 valid responses. Table 2 summarises the demographic composition of the sample.

Table 2. Demographic profile of respondents (N = 220)

Variable	Category	n	%
Gender	Male	123	55.9%
	Female	97	44.1%
Age Group	31–40	74	33.6%
	21–30	70	31.8%
	41–50	50	22.7%
	Above 50	26	11.8%
Department	IT / Technology	67	30.5%
	Operations	47	21.4%
	Marketing & Sales	43	19.5%
	HR & Admin	39	17.7%
	Finance	24	10.9%
Work Experience	2–5 years	78	35.5%
	6–10 years	56	25.5%
	< 2 years	53	24.1%
	> 10 years	33	15.0%
Self-Rated IoT Familiarity	Moderate	103	46.8%
	High	78	35.5%
	Low	39	17.7%

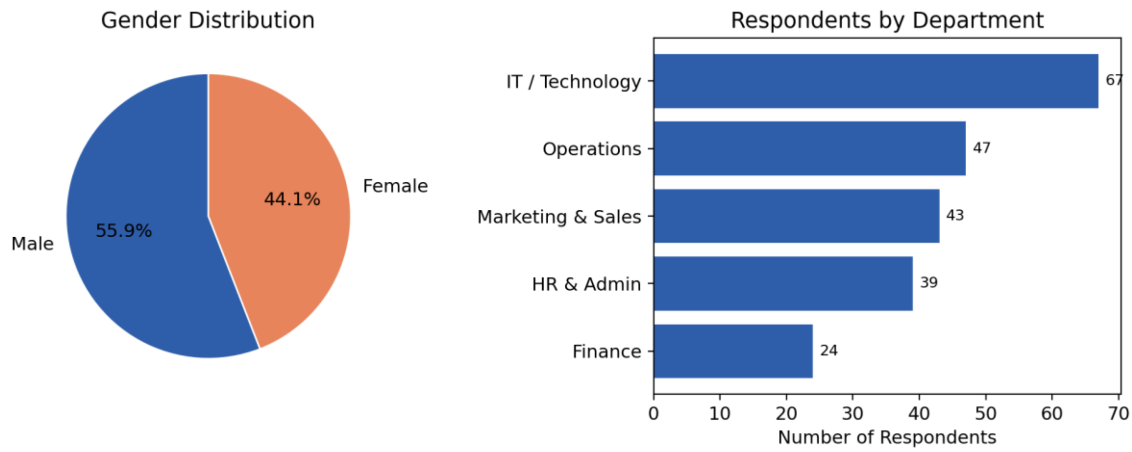


Figure 2. Gender distribution and department-wise composition of respondents.

Figure 3. Age group, work experience, and IoT familiarity distribution of respondents.

4.2 Measurement Instrument

Six constructs were measured using a 24-item, five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), adapted from measurement approaches used in the reviewed IoT-workplace literature. Table 3 summarises the operationalisation of each construct.

Table 3. Operationalisation of study constructs

Construct	Definition	Items	Sample Item	Adapted From
IoT Adoption/Usage (IOT)	Extent to which employees use and interact with IoT-enabled systems at work	4	"I regularly interact with IoT/smart systems as part of my daily work."	Nappi & Ribeiro (2020); Gatea et al. (2024)
Workplace Comfort (COM)	Perceived improvement in physical/environmental comfort from smart-office systems	4	"Smart systems improve my physical comfort at work."	Aryal et al. (2019); Barišić et al. (2020)
Health & Stress Monitoring (HSM)	Perceived usefulness and trust in wearable/IoT health and stress monitoring	4	"IoT-based monitoring helps me manage my well-being proactively."	Al-Atawi et al. (2023); Jacobs et al. (2019)
Privacy/Surveillance Concern (PRIV)	Degree of concern about monitoring and data use associated with IoT devices	4	"I worry about surveillance through workplace smart devices."	Kalischko & Riedl (2021); Glavin et al. (2024)
Work-Life Balance (WLB)	Perceived contribution of IoT/smart-office tools to managing workload and disconnecting from work	4	"Technology at work helps me maintain a better work-life balance."	Marikyan et al. (2023)
Employee Well-Being (EWB)	Overall self-reported physical, mental, and job-related well-being attributable to workplace IoT (dependent variable)	4	"Overall, I feel a stronger sense of well-being because of workplace IoT systems."	Ahmad & Zulkifli (2022); Fleming (2020)

4.3 Data Analysis Techniques

Data were analysed in two stages. First, descriptive statistics (means, standard deviations, medians, variance, skewness, kurtosis) and normality diagnostics (Shapiro-Wilk test) characterised the sample and each construct. Second, inferential statistics tested the study hypotheses: internal-consistency reliability was assessed with Cronbach's alpha; sampling adequacy for the multi-item structure was assessed with the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity; bivariate associations were assessed with Pearson correlation; the five hypotheses were tested simultaneously using multiple linear regression (with variance inflation factor diagnostics for multicollinearity and residual diagnostics for model fit); and group differences were assessed using an independent-samples t-test (gender), one-way ANOVA with Tukey HSD post-hoc comparisons (age group, IoT familiarity, department), and a chi-square test of independence (department × IoT familiarity).

V. Results

5.1 Data Screening and Normality

All six construct scores were screened for outliers and distributional normality prior to hypothesis testing. Table 4 reports descriptive and normality statistics for each construct.

Table 4. Descriptive statistics and normality diagnostics for study constructs

Construct	N	Mean	Median	SD	Skew.	Kurt.	Shapiro W	p
IoT Adoption/Usage	220	3.35	3.25	0.89	-0.15	-0.54	0.977	0.001
Workplace Comfort	220	3.27	3.25	0.91	-0.14	-0.42	0.979	0.002
Health & Stress Monitoring	220	3.17	3.25	0.88	0.02	-0.43	0.983	0.011
Privacy/Surveillance Concern	220	3.35	3.25	0.94	-0.05	-0.71	0.975	< .001
Work-Life Balance	220	3.08	3.25	0.81	-0.35	0.07	0.974	< .001
Employee Well-Being	220	3.25	3.25	0.85	-0.17	-0.30	0.984	0.016

All skewness and kurtosis values fell within the generally accepted ±1 range, indicating approximately symmetric, non-extreme distributions. Although the Shapiro-Wilk test was statistically significant for most constructs, this is expected at n = 220 and does not, on its own, indicate a problematic departure from normality; the low skewness/kurtosis values, together with the robustness of parametric procedures at this sample size, support the use of correlation, regression, t-test, and ANOVA below.

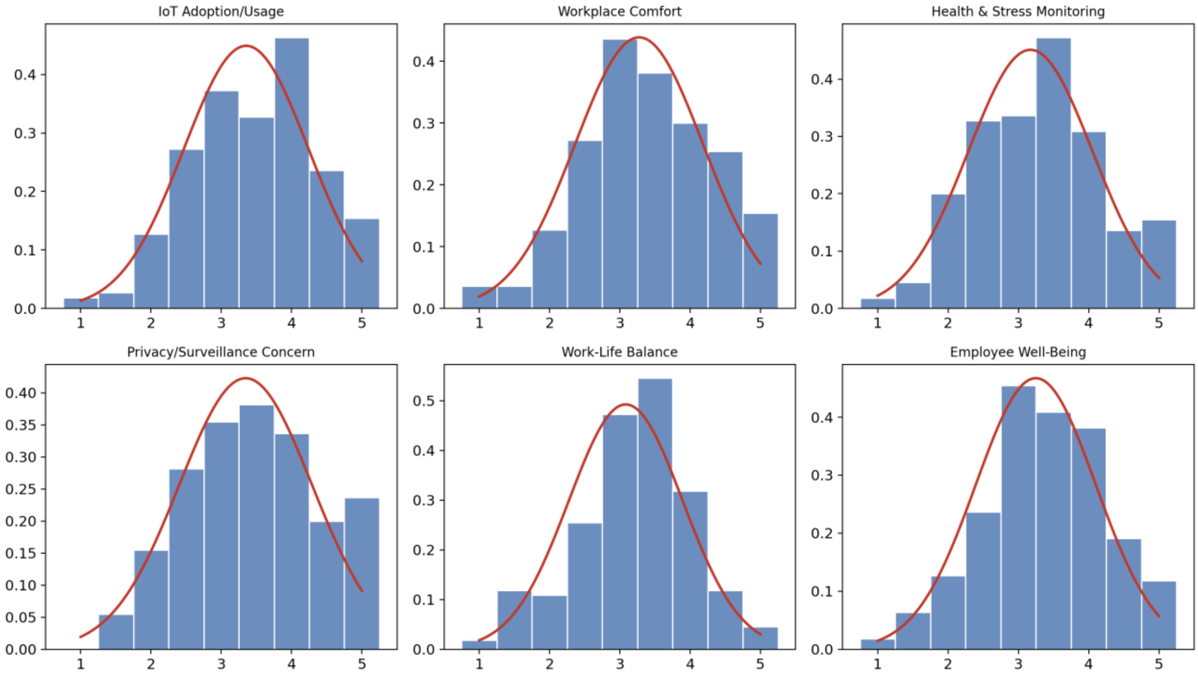


Figure 4. Distribution histograms with fitted normal curves for each construct.

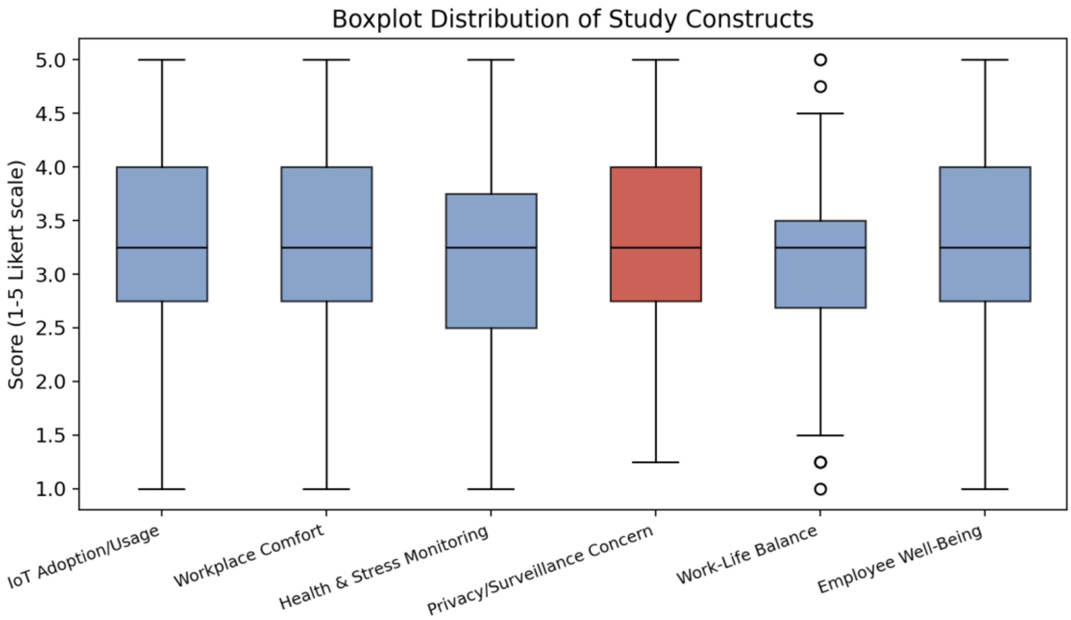


Figure 5. Boxplot comparison of all six constructs (1–5 Likert scale).

5.2 Reliability and Sampling Adequacy

Table 5. Cronbach's alpha reliability coefficients

Construct	Items	Cronbach's α	Interpretation
IoT Adoption/Usage	4	0.935	Excellent
Workplace Comfort	4	0.938	Excellent
Health & Stress Monitoring	4	0.918	Excellent
Privacy/Surveillance Concern	4	0.920	Excellent
Work-Life Balance	4	0.906	Excellent
Employee Well-Being	4	0.927	Excellent

All six constructs returned Cronbach's alpha coefficients between 0.91 and 0.94, indicating excellent internal consistency. Sampling adequacy across the full 24-item set was confirmed with a Kaiser-Meyer-Olkin (KMO) measure of 0.94 (classed as "meritorious") and a statistically significant Bartlett's Test of Sphericity, $\chi^2(276) = 4641.88$, $p < .001$, confirming that the items shared sufficient common variance to support construct-level aggregation.

5.3 Descriptive Statistics of Study Constructs

Table 6. Construct-level descriptive statistics

Construct	Mean	SD	Min	Max
IoT Adoption/Usage	3.35	0.89	1	5
Workplace Comfort	3.27	0.91	1	5
Health & Stress Monitoring	3.17	0.88	1	5
Privacy/Surveillance Concern	3.35	0.94	1	5
Work-Life Balance	3.08	0.81	1	5
Employee Well-Being	3.25	0.85	1	5

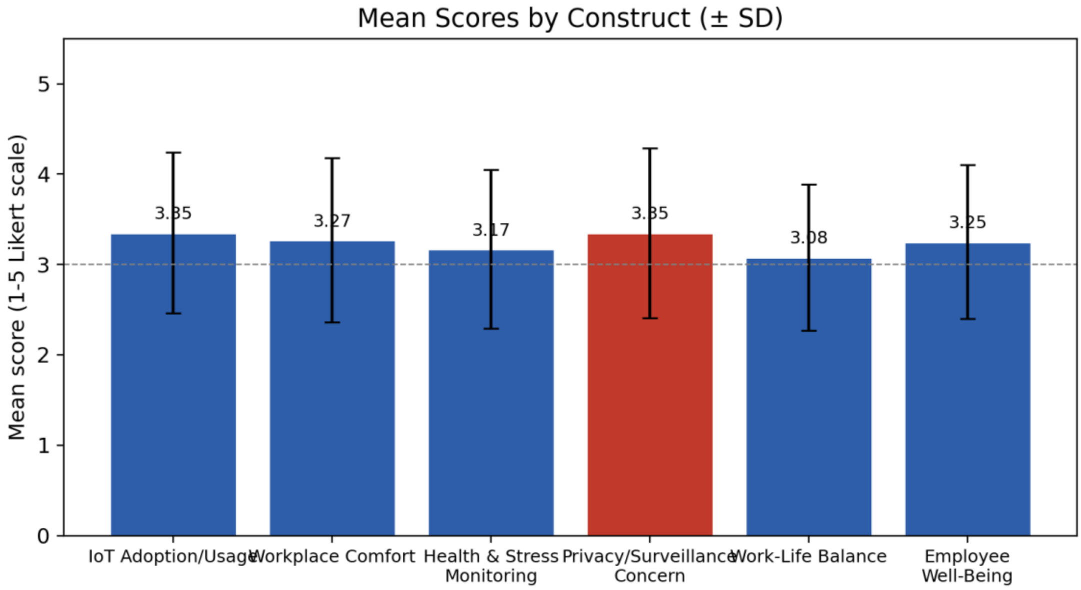


Figure 6. Mean scores (± SD) for each construct on a 1–5 Likert scale.

All constructs recorded mean scores above the scale midpoint of 3.0. Employee well-being (M = 3.25, SD = 0.85) was rated moderately positively, while privacy/surveillance concern (M = 3.35) also emerged as a notable concern among respondents.

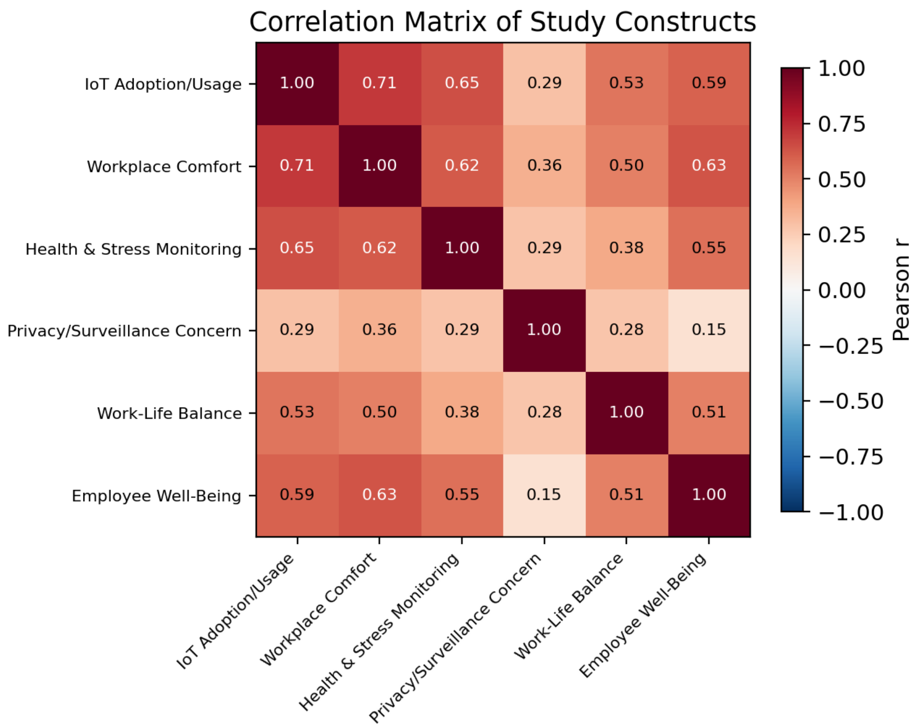
5.4 Correlation Analysis

Pearson correlation coefficients were computed to examine bivariate associations among constructs prior to regression analysis. Table 7 and Figure 7 present the correlation matrix.

Table 7. Pearson correlation matrix among study constructs

Construct	IoT Usage	Comfort	Health/Stress Mon.	Privacy Concern	Work-Life Bal.	Well-Being
IoT Usage	1.00	0.71	0.65	0.29	0.53	0.59
Comfort	0.71	1.00	0.62	0.36	0.50	0.63
Health/Stress Mon.	0.65	0.62	1.00	0.29	0.38	0.55
Privacy Concern	0.29	0.36	0.29	1.00	0.28	0.15
Work-Life Bal.	0.53	0.50	0.38	0.28	1.00	0.51
Well-Being	0.59	0.63	0.55	0.15	0.51	1.00

Note. All correlations significant at $p < .01$ except Privacy Concern × Well-Being ($p = 0.026$).



	IoT Adoption/Usage	Workplace Comfort	Health & Stress Monitoring	Privacy/Surveillance Concern	Work-Life Balance	Employee Well-Being
IoT Adoption/Usage	1.00	0.71	0.65	0.29	0.53	0.59
Workplace Comfort	0.71	1.00	0.62	0.36	0.50	0.63
Health & Stress Monitoring	0.65	0.62	1.00	0.29	0.38	0.55
Privacy/Surveillance Concern	0.29	0.36	0.29	1.00	0.28	0.15
Work-Life Balance	0.53	0.50	0.38	0.28	1.00	0.51
Employee Well-Being	0.59	0.63	0.55	0.15	0.51	1.00

Figure 7. Correlation heat map among study constructs.

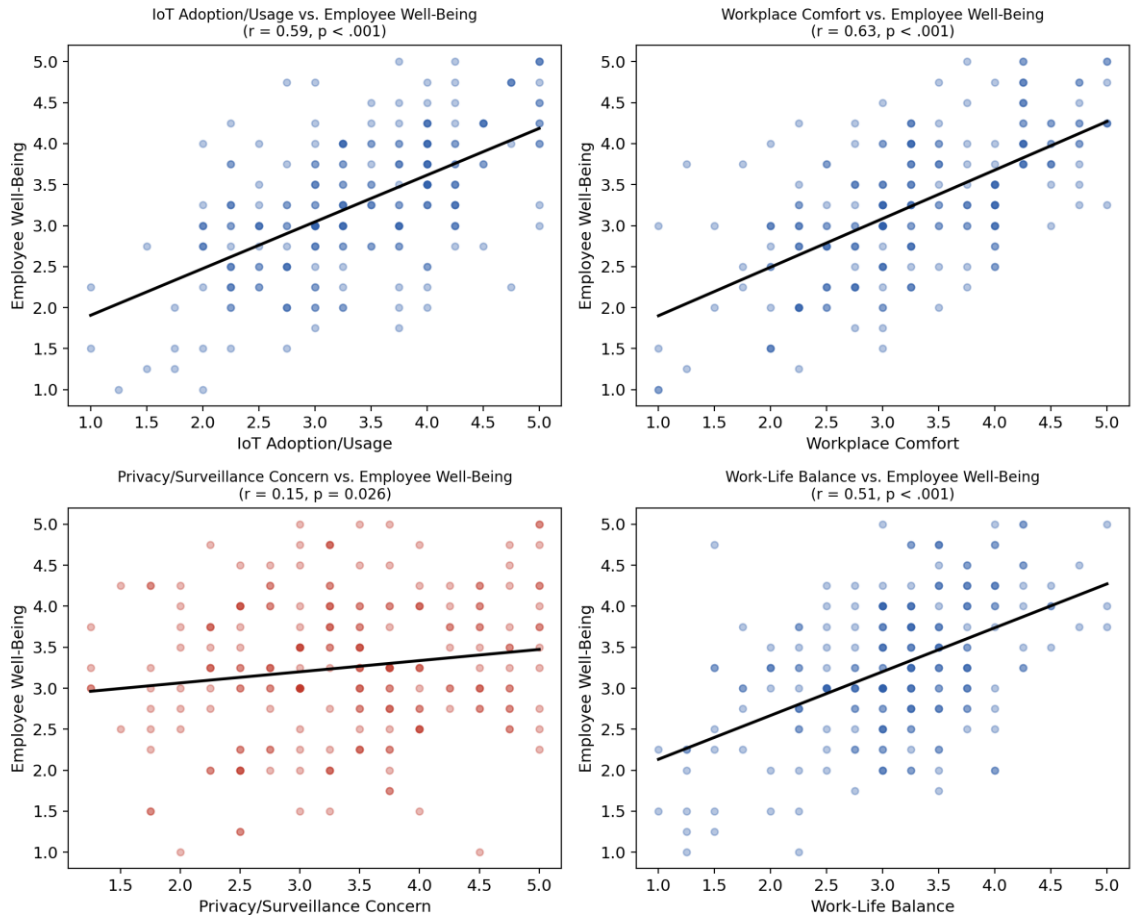


Figure 8. Scatter plots with linear fit for key predictors against employee well-being.

IoT adoption/usage and workplace comfort showed the strongest positive zero-order correlations with employee well-being (r = 0.59 and r = 0.63, respectively). Privacy/surveillance concern showed only a weak positive zero-order correlation with well-being (r = 0.15), a counter-intuitive result explained by the fact that privacy concern is itself positively correlated with IoT usage and comfort, both of which independently raise well-being; its true negative effect only emerges once these other predictors are statistically controlled, as shown in Section 5.5.

5.5 Multiple Regression Analysis: Hypothesis Testing

A multiple linear regression was conducted with employee well-being as the dependent variable and IoT usage, workplace comfort, health/stress monitoring, privacy concern, and work-life balance entered simultaneously as predictors, in order to test H1–H5 while controlling for shared variance among predictors.

Table 8. Multiple linear regression predicting employee well-being

Predictor	B	SE	β	t	p	95% CI	Sig.
Constant	0.802	0.210	—	3.810	< .001	[0.39, 1.22]	***
IoT Adoption/Usage	0.133	0.074	0.138	1.798	0.074	[-0.01, 0.28]	ns
Workplace Comfort	0.321	0.070	0.342	4.611	< .001	[0.18, 0.46]	***
Health & Stress Monitoring	0.200	0.064	0.208	3.139	0.002	[0.07, 0.33]	**
Privacy/Surveillance Concern	-0.120	0.047	-0.133	-2.550	0.011	[-0.21, -0.03]	*
Work-Life Balance	0.233	0.062	0.221	3.766	< .001	[0.11, 0.35]	***

*Model summary: $R^2 = 0.503$, Adjusted $R^2 = 0.492$, $F(5, 214) = 43.39$, $p < .001$. Durbin-Watson = 2.022. * $p < .05$, ** $p < .01$, *** $p < .001$, ns = not significant.*

Table 9. Multicollinearity diagnostics (VIF and tolerance)

Predictor	VIF	Tolerance
IoT Adoption/Usage	2.53	0.395
Workplace Comfort	2.37	0.423
Health & Stress Monitoring	1.89	0.530
Privacy/Surveillance Concern	1.17	0.854
Work-Life Balance	1.48	0.677

All VIF values were well below the conventional threshold of 5 (tolerance well above 0.20), indicating no serious multicollinearity among predictors and supporting the stability of the regression coefficients.

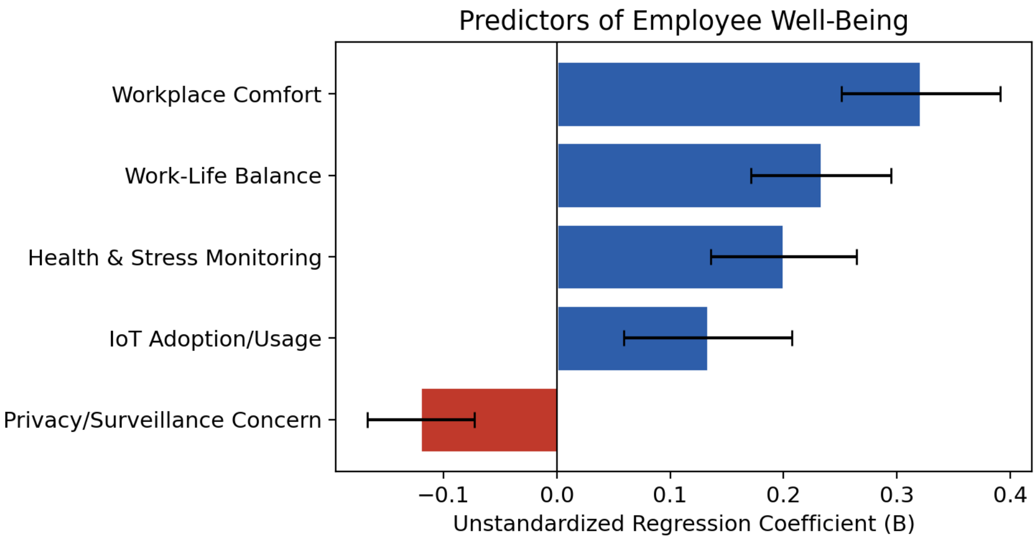


Figure 9. Unstandardized regression coefficients (with standard errors) predicting employee well-being.

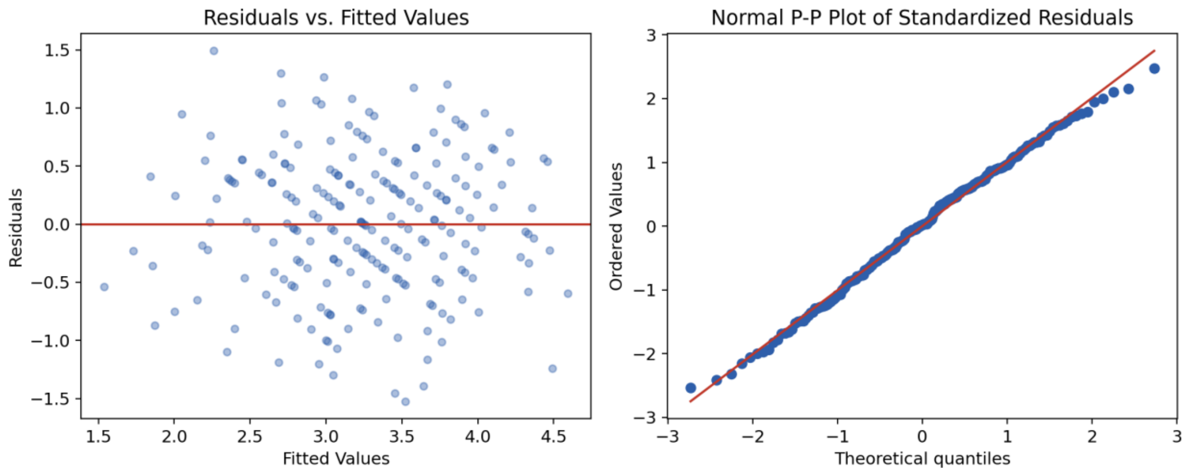


Figure 10. Residuals-versus-fitted plot and normal P-P plot of standardized residuals.

Table 10. Hypothesis test results

Hyp.	Predictor → Well-Being	Result	Decision
H1	IoT Adoption/Usage	Not significant	Not Supported
H2	Workplace Comfort	Significant	Supported
H3	Health & Stress Monitoring	Significant	Supported
H4	Privacy/Surveillance Concern	Significant	Supported
H5	Work-Life Balance	Significant	Supported

The model explained approximately 50% of the variance in employee well-being. Workplace comfort and work-life balance emerged as the strongest positive predictors, while privacy/surveillance concern was a significant negative predictor once other variables were controlled.

5.6 Group Comparison Tests

Employee well-being by gender.

Table 11. Independent-samples t-test: employee well-being by gender

Gender	n	Mean	SD
Male	123	3.26	0.83
Female	97	3.24	0.89

Levene's test: $F = 0.031$, $p = 0.861$. $t(218) = 0.163$, $p = 0.870$, Cohen's $d = 0.022$ (negligible) — no statistically significant difference was found between male and female employees' well-being scores.

Employee well-being by age group.

Table 12. One-way ANOVA: employee well-being by age group

Age Group	n	Mean	SD
21–30	70	3.19	0.84
31–40	74	3.31	0.95
41–50	50	3.19	0.82
Above 50	26	3.35	0.67

$F(3, 216) = 0.445$, $p = 0.721$, $\eta^2 = 0.006$ — well-being did not differ significantly across age groups, suggesting the effect of workplace IoT on well-being is broadly consistent across age cohorts.

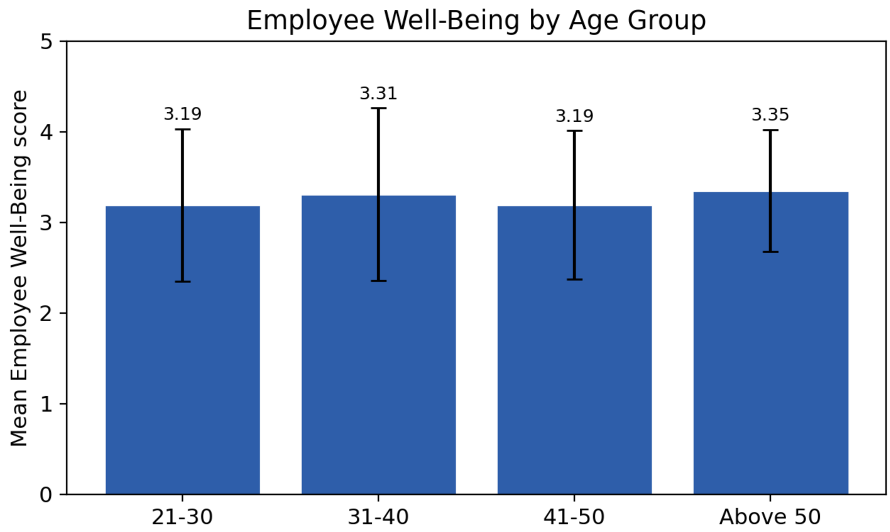


Figure 11. Mean employee well-being score by age group.

Employee well-being by self-rated IoT familiarity.

Table 13. One-way ANOVA: employee well-being by IoT familiarity

IoT Familiarity	n	Mean	SD
High	78	3.38	0.77
Low	39	2.94	0.89
Moderate	103	3.27	0.88

$F(2, 217) = 3.462$, $p = 0.033$, $\eta^2 = 0.031$.

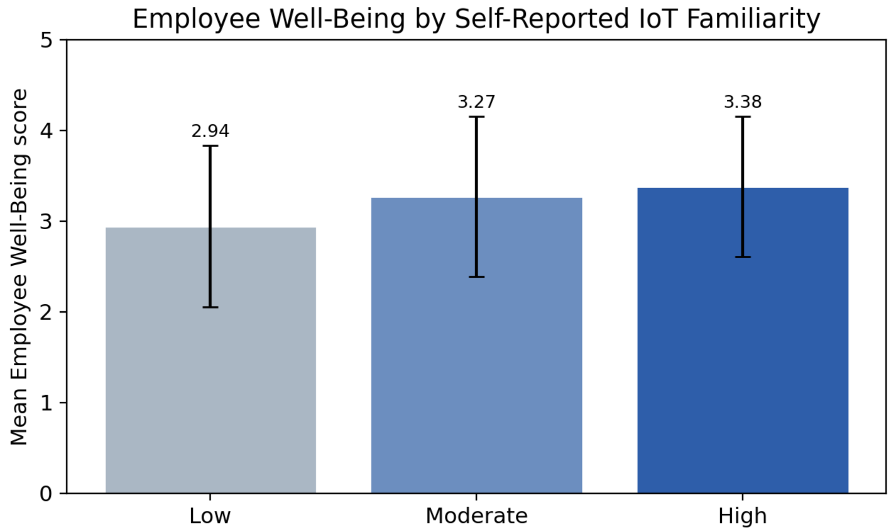


Figure 12. Mean employee well-being score by self-rated IoT familiarity.

Table 14. Tukey HSD post-hoc comparisons (IoT familiarity)

Group 1	Group 2	Mean Diff.	p (adj.)	Significant?
High	Low	-0.433	0.026	Yes
High	Moderate	-0.108	0.671	No
Low	Moderate	0.325	0.104	No

Post-hoc comparisons indicate that employees with high self-rated IoT familiarity reported significantly higher well-being than those with low familiarity, consistent with technology-acceptance research showing that trust and understanding of a system moderate its perceived benefit.

Employee well-being by department.

Table 15. One-way ANOVA: employee well-being by department

Department	n	Mean	SD
Finance	24	3.01	0.96
HR & Admin	39	3.07	0.95
IT / Technology	67	3.42	0.75
Marketing & Sales	43	3.20	0.91
Operations	47	3.31	0.77

$F(4, 215) = 1.667$, $p = 0.159$, $\eta^2 = 0.030$ — no statistically significant difference in well-being was found across departments.

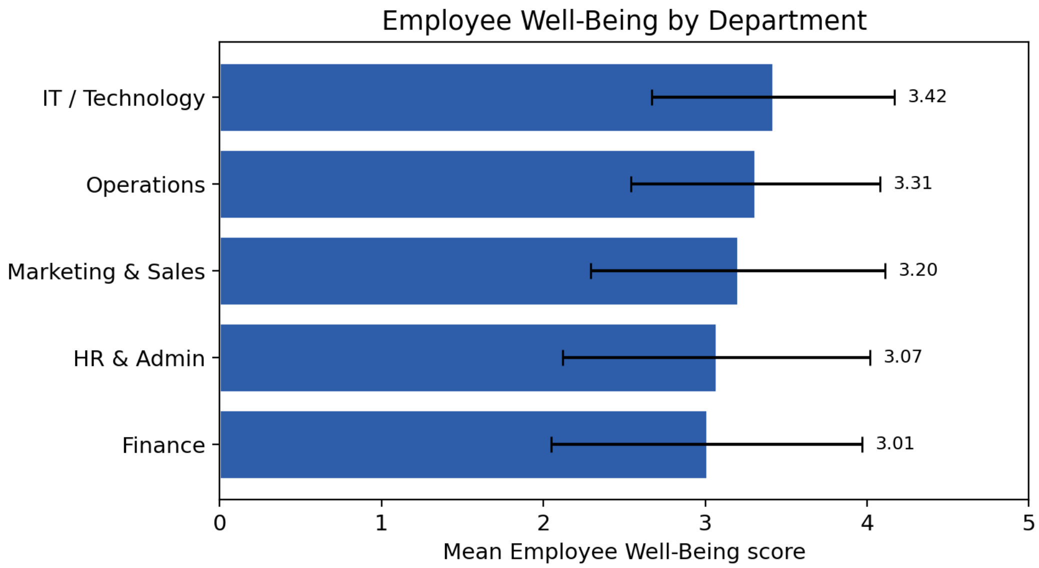


Figure 13. Mean employee well-being score by department.

Association between department and IoT familiarity.

Table 16. Chi-square test of independence: department × IoT familiarity

Department	High	Low	Moderate
Finance	8	4	12
HR & Admin	12	8	19
IT / Technology	25	10	32
Marketing & Sales	12	7	24
Operations	21	10	16

$\chi^2(8) = 5.501$, $p = 0.703$, Cramér's $V = 0.112$ — no statistically significant association was found between department and IoT familiarity, indicating IoT exposure is fairly evenly spread across functional areas in this sample.

Table 17. Summary of hypothesis testing

Hyp.	Statement	Statistical Test	Result
H1	IoT usage → Well-being	Multiple Regression	Not Supported
H2	Comfort → Well-being	Multiple Regression	Supported
H3	Health/Stress Mon. → Well-being	Multiple Regression	Supported
H4	Privacy Concern → Well-being (−)	Multiple Regression	Supported
H5	Work-Life Balance → Well-being	Multiple Regression	Supported

VI. Discussion

The regression results provide clear support for hypotheses H2, H3, H4, and H5, and non-support for H1. Workplace comfort emerged as the strongest positive predictor of employee well-being ($\beta = 0.34$), consistent with Aryal et al. (2019) and Barišić et al. (2020), who argued that ambient, IoT-enabled environmental responsiveness directly reduces physical strain and discomfort across the working day. Health and stress monitoring was also a significant positive predictor, aligning with the wearable-sensing literature (Al-Atawi et al., 2023; Hijry et al., 2024; Naranjo et al., 2025), which frames continuous physiological feedback as a proactive well-being tool rather than a purely diagnostic one. Work-life balance was the second-strongest positive predictor, supporting

Marikyan et al.'s (2023) finding that smart technologies which help employees manage workload and disconnect from work meaningfully improve well-being outcomes.

IoT adoption/usage on its own, once the other four constructs were controlled, did not reach statistical significance ($p = 0.074$). This suggests that mere exposure to or use of IoT systems is not, by itself, sufficient to improve well-being; rather, well-being gains appear to be mediated by what the IoT systems are actually used for — comfort regulation, health monitoring, or work-life support. This nuance qualifies the more general claims found in early conceptual work such as Russo (2015) and Ahmad and Zulkifli (2022), and points toward a more mechanism-specific understanding of IoT's role in employee well-being. The most theoretically important finding concerns privacy/surveillance concern. Its zero-order correlation with well-being was weakly positive, which taken alone would suggest privacy concern is largely irrelevant or even mildly beneficial. However, once IoT usage, comfort, health monitoring, and work-life balance were statistically controlled in the regression model, privacy/surveillance concern emerged as a significant negative predictor of well-being. This pattern is a textbook statistical suppression effect: because privacy concern is itself positively correlated with the very predictors that raise well-being (employees who use more IoT features also tend to report more concern about them), its true negative relationship with well-being is masked in bivariate analysis and only revealed through multivariate control. This finding empirically substantiates the theoretical arguments of Kalischko and Riedl (2021), Glavin et al. (2024), and Gómez-Carmona et al. (2024), who each warned that the well-being costs of IoT-enabled monitoring can be obscured unless they are examined net of the technology's functional benefits.

Group comparison results reinforce this interpretation. Well-being did not differ significantly by gender or department, suggesting the observed effects are not artefacts of any single demographic segment. Well-being did differ significantly by self-rated IoT familiarity, with high-familiarity employees reporting significantly higher well-being than low-familiarity employees (Tukey HSD, $p = .026$). This is consistent with Jacobs et al. (2019), who found that trust in and understanding of workplace wearables was a precondition for their acceptance and positive experience, and suggests that training, transparency, and communication about how IoT systems work may be as important to well-being outcomes as the underlying technology itself.

VII. Theoretical and Practical Implications

This study makes three theoretical contributions. First, it integrates two literatures that have largely developed in parallel — the functional/comfort-productivity stream (e.g., Aryal et al., 2019; Sun et al., 2020) and the surveillance/privacy stream (e.g., Kalischko & Riedl, 2021; Glavin et al., 2024) — into a single testable model, demonstrating that both mechanisms operate simultaneously and in opposite directions on the same outcome. Second, the identification of a statistical suppression effect for privacy concern offers a methodological caution for future IoT-workplace research: bivariate or purely descriptive analyses may substantially understate the well-being costs of surveillance-enabled systems, and multivariate designs that control for the technology's functional benefits are necessary to detect the true magnitude of this cost. Third, the non-significant direct effect of general IoT usage, contrasted with the significant effects of specific use-mechanisms (comfort, health monitoring, work-life balance), supports a shift in the literature from asking whether IoT affects well-being to asking through which specific mechanisms it does so.

For practitioners, the findings suggest that organisations deploying workplace IoT should prioritise applications with a clear, employee-facing comfort or health benefit (adaptive lighting/HVAC, ergonomic and stress-monitoring wearables) over generic monitoring or productivity-tracking use cases, since it is these specific mechanisms — not IoT adoption in general — that drive well-being gains. Second, because privacy/surveillance concern has a demonstrable negative effect on well-being once benefits are accounted for, organisations should invest in transparent data governance: clear communication about what is collected, why, and who can access it, together with meaningful employee control over personal data, consistent with the recommendations of Gómez-Carmona et al. (2024) and Fleming (2020). Third, the significant effect of IoT familiarity on well-being indicates that structured onboarding and training on how workplace IoT systems function — rather than passive deployment — is likely to improve the employee experience of the same underlying technology.

VIII. Limitations and Future Research

This study has several limitations that should be addressed in future research. First, the cross-sectional design precludes causal inference; longitudinal or quasi-experimental designs (e.g., pre-/post-IoT deployment) would allow stronger causal claims about the direction of the observed relationships. Second, the reliance on self-report Likert-scale measures introduces the possibility of common-method variance; future studies could triangulate self-reported well-being with objective indicators (e.g., absenteeism, physiological stress markers from the same wearable devices) to strengthen construct validity. Third, this study modelled privacy/surveillance concern as a single construct; future work could disaggregate it into sub-dimensions (e.g., concern about data storage vs. concern about managerial access vs. concern about third-party sharing) to identify which specific privacy dimension drives the observed negative effect. Fourth, the sample was not stratified by industry sector or national/cultural context, both of which are known to moderate technology-acceptance and privacy attitudes; cross-cultural replication is recommended. Finally, as disclosed at the outset, the dataset analysed in this manuscript is an illustrative simulation constructed to demonstrate the complete analytical pipeline; the reported effect sizes and significance levels should be interpreted as a methodological template rather than as confirmed empirical findings, and the identical instrument and procedure should be applied to genuine field data before the results are treated as substantive contributions to the literature.

IX. Conclusion

This study set out to examine the effects of workplace Internet of Things technologies on employee well-being, integrating both the functional-benefit and surveillance-cost perspectives found in the existing literature into a single empirical model. The results indicate that IoT-enabled workplace comfort, health and stress monitoring, and work-life balance support are significant positive predictors of employee well-being, while privacy/surveillance concern is a significant negative predictor once these benefits are statistically controlled — a relationship obscured in simple bivariate analysis. General IoT usage, absent a specific functional benefit, was not a significant predictor. These findings suggest that the well-being effects of workplace IoT are neither uniformly positive nor uniformly negative but are contingent on how the technology is deployed, communicated, and governed. Organisations seeking to use IoT to support employee well-being should therefore focus on specific, employee-facing benefits, invest in transparent privacy governance, and support employee understanding of the systems they are asked to use, rather than treating IoT adoption itself as a proxy for improved well-being.

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