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# AI-DRIVEN INTERVENTIONS FOR WORKPLACE WELLNESS AMONG FEMALE FAST-FOOD EMPLOYEES IN CANADA

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***Abstract***

*While convenience and affordability appear to be key components of the fast-food industry in Canada, the industry hides harsh working conditions, especially for women. This study seeks to assess how effective AI-based workplace wellness interventions reduce stress and increase job satisfaction and work-life balance among female fast-food workers in Canada. This mixed-methods design study comprises 300 female fast workers employed in six Canadian cities to assess the impact of a 12-week AI-based wellness program on stress, job satisfaction, work-life balance, and digital health literacy among participants. Quantitative data were analysed using t-tests, ANOVA, regression, and mediation on SPSS and AMOS, and qualitative insights gained from 25 post-intervention interviews were thematically analyzed using NVivo to place the psychological and experiential dimensions of AI tool engagement in context. AI-based wellness interventions have been introduced to the participants, where they gain noticeable changes according to the measured results. The study respondents show a significant reduction in perceived stress and improvement in job satisfaction, work-life balance, digital health literacy, and AI-trust after the AI-based intervention with great effect sizes and strong predictive relationships ($R^2 = 0.51$). Mediators and moderators' analyses confirmed that trust in AI partially mediates the relationship between work-life balance and stress, while digital health literacy reinforced the positive relation between work-life balance and job satisfaction. Interviews were thematically analysed, leading to five interconnected themes: psychological well-being, technology usability, managerial support, improved work-life balance, and privacy concerns. These themes highlight the very nuanced experiences of women using AI tools in precarious labour contexts.*

***Keywords:*** *AI-based Wellness Interventions, Female Fast-food Workers, Occupational Stress, Work-Life Balance, Digital Health Literacy, Trust in AI, Canada.*

## 1. INTRODUCTION

The modern fast-food industry in Canada represents the extreme in convenience and price availability to its customers (Kumolu-Johnson, 2024). While presenting that facade, it hides the harsh realities faced by those who run all the operations within it. With about 1.1 million people as of 2024 working in the food services and accommodations sectors, this remains an important avenue for employment, especially for women, newcomers, and economically vulnerable people (Scott, 2024; Statistics Canada, 2024). Women constitute over 60 percent of the female workforce of the quick-service restaurant sector (Escoffier, 2024).

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They tend to be in positions that generally pay them minimal wages, deny them an opportunity to work in regular hours, present them with an extraordinary amount of customer pressure, and offer a very narrow scope of upward mobility.

Thus, female fast-food employees often undergo occupational stress levels above the norm, burnout, and some mental health distress (Grimmond et al., 2024). Statistics Canada and the Canadian Centre for Occupational Health and Safety reported that more than 45% of women working in food services cite stress due to their jobs, while 32% deal with anxiety of work intensity and clashes with scheduling (Statistics Canada, 2023). These figures, implying a massive mental health crisis in the low-wage service sector, also thrust the glaring reality of structured workplace wellness interventions that take into account the needs of women in these kinds of environments.

With AI-powered tools like digital mental health chatbots, biometric fatigue trackers, predictive scheduling algorithms, and wellness monitoring apps, AI technologies already appear to be managing stress and ensuring the productivity of professionals in many professional fields, with early burnout detection going on among employees (Reynoso, 2025; Bapna & Ghose, 2024). However, in the fast-food sector of Canada, with special attention to female employees in entry-level positions, such interventions are hardly integrated and little researched.

Despite policy narratives promoting digital transformation across sectors, almost no data exists on how these technologies impact the specific psychosocial realities of female workers. This digital divide not only amplifies workplace health inequities based on gender but raises urgent issues regarding access, trust, and cultural relevance in AI applications in blue-collar, gendered labour markets.

The COVID-19 pandemic intensified the urgency of dealing with mental health and workplace wellness within the fast-food industry (Galon, 2021). Essential workers, most of whom are women, in the fast-food sector were at a higher risk of exposure, experienced staffing shortages, emotional exhaustion, and additional burden of work obligations (Lippert et al., 2020). The post-pandemic staffing shortages have added pressure, while inflation increases in the cost-of-living have diminished their real income and economic security (Hill & Webber, 2022).

All these factors create an environment where burnout related to stress, job dissatisfaction, and attrition of employees is on the rise. In this context, AI-based wellness interventions are a hopeful but limited opportunity to reimagine health in workplace settings within the service sector. More than mechanization or surveillance, digital assistance offers workers functional support (Berg, 2019), and examples such as AI mental health chatbots, shift scheduling optimizers, and predictive fatigue tracking apps have shown effective results (Rudroff, 2024). They offer workers an accessible, customizable, and stigma-free resource as mental health and workplace stressors arise.

Though the use of AI in the Canadian labour market is on the rise, existing research that examines the nexus of artificial intelligence, workplace wellness, and gender among fast-food workers is surprisingly limited. Most current knowledge about AI and workplace wellness is placed in a corporate or clinical context, with a scarcity of evidence on the application of AI within frontline workers, particularly women workers in fast food (Horan et al., 2021).

Current knowledge about women's labor in fast food is largely focused on wage inequality, harassment, or scheduling practices, yet few examine the interface between technology and addressing challenges for women interior to fast-food jobs. Therefore, further context-sensitive, gender-focused, technology-based research is needed to think through how AI was used ethically and effectively to promote well-being for women in precarious work.

In this context, the present research assess the effects of AI-based workplace wellness interventions on stress, job satisfaction, and work-life balance for female fast-food employees in Canada.

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The aims of the study are four-pronged:

- To determine the efficacy of AI-based wellness interventions for lessening perceived stress and increasing job satisfaction for women in fast-food work positions.
- To examine the benefits of AI technologies in considering and supporting work-life balance for low-wage work with unpredictable shift structures and related burden.
- To investigate the moderating role of digital health literacy and the potential mediating role of trust in AI in the success of health and wellness interventions.
- To provide practical insights into how AI-based wellness interventions/designs could be designed, modified, and scaled for gender-equitable distribution across the fast-food industry.

## 2. LITERATURE REVIEW

Recent scholarship has focused increasingly on the relationship between AI, mental health, and workplace wellness, offering important insights into how AI-enabled tools may reimagine occupational well-being. For instance, Omose and Ikuyinminu (2024) investigated the capacity of AI-enabled predictive analytics as a transformative mechanism for organizations to proactively track and address employee burnout. The framework employed by the authors included ethical data collection and real-time monitoring, explainable AI modelling, and collaboration with healthcare providers and HR platforms. Their research exemplified how artificial intelligence could enable organizations to implement timely and evidence-based interventions in corporate wellness systems through integrated feedback loops and physiological metrics. Naik et al. (2025) also examined the potential of artificial intelligence for early burnout detection through predictive analytics, biometric tracking, and sentiment analysis. Their findings introduced eco-volunteering as a therapeutic post-intervention activity, raising the prospect that a combination of AI tracking and restorative nature-based programs could enhance when implemented in future strategies for employee satisfaction and engagement.

Tito et al. (2025) added a qualitative dimension by conducting detailed interviews in high-stress contexts (healthcare, education, finance) to examine users' attitudes towards AI chatbots and wearable devices. They found that AI-chatbots offered stigma-free and easy access to emotional support while the wearables equipped users to become aware of their stress indicators of sleep variability and heart rate variability. Potential adoption issues included perceived usefulness, cultural appropriateness, trust, and data privacy. This is in some agreement with Khan (2024) who quantitatively studied AI technologies' effects on women employees' work-life balance in the hotel industry in Delhi, stating productivity and efficiency increased but there were other issues around job uncertainty and digital fatigue for employees, and women employees in particular, working in high-demand service industries. This phenomenon is also surfacing in the work of Mantello et al. (2023), who suggest that the empathic AI tools used for emotion knowledge have concern for increasing the stress levels of those experiencing marginalization. Using a global survey and a Bayesian-based analysis, they found that East Asian respondents held a more positive attitude towards emotion AI (EAI) than Western respondents, who were more critical regarding issues related to algorithmic bias, surveillance, and weakening worker autonomy.

Bisht and Uniyal (2024) provided an industry-wide overview of how AI and Internet of Things (IoT) tools were changing employee job satisfaction. They determined that job satisfaction could be enhanced with AI-supported automation, meaning that AI-supported improved decision making, reducing cognitive load, through the use of real-time analytics and designs that were centered on human decision making. They conducted a series of sector-based case studies in healthcare and manufacturing. One conclusion was that organizations achieved productive and engaged employees

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by building new adaptive policies and introducing upskilling programs. In a related study, Meharunisa et al. (2024) evaluated the effects of AI capabilities on work-life balance and female empowerment in Saudi Arabian universities. Their study used a structural equation modelling (SEM) approach, which demonstrated that the ability to use AI infrastructure with agility created management capability, conceptualizing and describing enhanced perceptions of empowerment and institutional efficiency for female faculty members. In addition to accounting for the variables involving this complexity, the authors considered moderators that were age, education, and marital status. All or nearly all contribute to the complex sociotechnical dynamics involved in the adoption of AI tools.

Xu et al. (2023) provided a cautionary perspective on the mental health implications using (Conservation of Resources theory. Their findings suggested that AI awareness was positively related to employee depression through emotional exhaustion. The important piece of their research, related to perceived organizational support as a moderator to weaken the relationship between emotional exhaustion and depression, underlined the importance of supportive environments as a psychological safety net against the risks of AI surveillance and the anxiety towards automation. Overall, Xu et al. put forward the argument that while AI awareness has the potential to help employees through anticipatory behaviours, AI awareness also has the potential to increase stress without proper institutional guidance and structures in place to stabilize that risk.

All of these studies shared the theme of trust and user acceptability of new technology. In their study, Tito et al. (2025) argued that digital trust was a prerequisite for the adoption of chatbots and wearables in the workplace, particularly for employees who might be worried that they were being monitored. Omose and Ikuyinminu (2024) also supported the case for trust through developing transparent and explainable AI-based models. Also, in Mantello et al.'s (2023) research, there was mention of concerns that the unregulated use of empathic surveillance, for example, innumerable use cases, might violate emotional privacy and worsen inequalities along factors such as race, gender, and class. More generally, the literature raises ethical questions about the limits of AI in the workplace and how the potential for algorithmic biases might lead to forms of discrimination.

Another commonality within these studies was the gendered aspect of AI adoption. Khan (2024) and Meharunisa et al. (2024) centered their studies on women workers and faculty members, respectively, noting empowerment opportunities, but persistent institutional barriers to this empowerment. While AI tools could help automate repetitive work tasks and provide more flexibility (i.e., flexibility is in employee choice), employees also reported an increase in digital identity, and that distinctions between work and home were often unclear, especially in service industries. For a female worker in fast food, these issues are relevant due to the nature of shift work in service industries in balance caregiving, and the capacity to upskill (low rates of digital literacy). Bisht and Uniyal (2024) proposed continuous upskilling and adaptive policy adjustments to offset the issues of digital identity and employee workload from new AI tools, but indicated that all interventions are context-dependent and, when designing solutions, must be inclusive.

In brief, the existing literature reminded researchers of both the transformative opportunity and substantial limitations of AI-powered interventions in workplace wellness. Although interest in AI-designed workplace wellness has increased, research to date has emphasized corporate or academic contexts, ignoring low-waged service workers, such as fast-food workers, and their experiences of unique stressors, limited digital knowledge, and reduced access to mental health supports. Additionally, previous research has not combined AI interventions within a strong mixed-methods evaluation and has rarely given attention to trust, usability, and equity issues for AI on-site. This study fills this gap by implementing and evaluating an AI-enhanced wellness program with female fast-food workers in Canada and gives empirical knowledge and practical guides for inclusive, ethical, and scalable mental health interventions.

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### 2.1. Theoretical Framework and Hypothesis Development

In today's labor markets, which are characterized by factors like high demand and low autonomy, including those in the fast-food sector, worker wellness has received significant attention from researchers and policy-makers in organizations (Sorensen et al., 2021). To establish a robust framework to understand the mechanisms through which these interventions, and their outcomes, are conceptualized, this research has been theoretically framed using two complementary models, the Job Demands-Resources (JD-R) theory (Bakker & Demerouti, 2014) and the Technology Acceptance Model (TAM) (Davis et al., 1989). The Job Demands-Resources (JD-R) theory suggests that employee well-being is determined by the balance between job demands and job resources (Bakker & Demerouti, 2018). Job demands are those aspects of the job that involve physical, psychological, social, or organisational aspects of the job that require sustained effort and are associated with physiological or psychological cost (Bakker & Demerouti, 2017). Job resources instead are those aspects of the job that are physical, psychological, social, or organizational and help an individual achieve work goals, reduce job demands, or stimulate personal growth and development (Schaufeli, 2017). Working in fast-food employment is characterized by high job demands, including extended periods at work, working under time pressure, emotional labour when working with customers, variable or unpredictable time schedules, or limited ability to control work conditions.

AI-driven wellness tools—examples of which include mental health chatbots, digital fatigue monitors, AI scheduling, and apps that track wellness—are newly emerging job resources in the JD-R background (Pandey et al., 2005). These resources foster employee wellness by reducing the burden of job demands and by providing supportive tools for coping and recovery. Thus, according to the JD-R theory, these AI tools mediate stressors associated with job demands to promote enhanced wellness outcomes (Arboh et al., 2025). According to this model, the study's first hypothesis (H1) argues that

H1: AI-based workplace wellness, such as job satisfaction, work-life balance, and trust, significantly reduces perceived stress for female fast-food employees.

The AI tools have the potential to act as digital resources for employees in managing their mental and physical workload, and are therefore expected to lessen the stress of having high job demands (Rožman et al., 2023). Moreover, as predicted by JD-R, any extra access to resources bring positive motivational/relational outcomes such as higher engagement and job satisfaction (Vermooten et al., 2021). The second hypothesis (H2) of the study states that,

H2: AI-based wellness, such as work-life balance and trust, positively influences job satisfaction, especially through instilling care, control, and emotional support in what is often a highly demanding job.

Another extension of JD-R offers the effect of job demands and job resources on spillover effects to personal life (Abdou et al., 2024). Fast-food workers, especially women, struggle with work-life balance when faced with controlling schedules, unforeseen schedule changes, or undertaking these jobs as supplemental/secondary income work. AI scheduling optimization tools that eliminate unexpected demands and allow employees control over their preferences were considered a job resource that contributes to work-life balance (George, 2024). Therefore, the third hypothesis (H3) states that

H3: Improved work-life balance supported by AI tools provides a positive impact on work-life balance and reduces perceived stress for female fast-food workers.

The TAM posits that two key beliefs—perceived usefulness and perceived ease of use—predict an individual’s attitude toward using technology that subsequently informs behavioral intention and actual use (Hess et al., 2014). Importantly, the adoption of AI-driven wellness tools by female fast-

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food employees is not only defined by their availability, but rather by users' cognitive appraisals of the tools' utility and usability. Female employees in fast-food contexts experience gaps in digital literacy, are worried about privacy, and are doubtful of automation, particularly when tech seems to encroach on their well-being or choice (Khanna, 2022). For this reason, using TAM in this study better accounts for variation in engagement with AI tools. The fourth hypothesis (H4) states that.

H4: AI tools' trust is positively associated with continued usage intention and reduced stress.

Moreover, expanding on TAM literature introduces the construct of trust in AI, which is especially useful for wellness-related tools because of the sensitive nature of emotional and health data users provide (Chen et al., 2024). Trust in AI includes beliefs regarding the system's reliability, integrity, and benevolence, as it relates to data and results users obtain from the AI tool (Ryan, 2020). If women employees do not have trust in the AI tool because of concerns regarding data misuse, impersonality, and algorithmic bias, then the chances of meaningful engagement are slim. Therefore, the fifth hypothesis (H5) states that.

H5: Trust in AI mediates the relationship between work-life balance and stress reduction for improved wellness outcomes.

In addition to that, technological engagement is not a separate occurrence within an isolated space. It is contingent upon people's capacities, such as digital health literacy, which is defined as the ability to search for, understand, appraise, and apply health information from digital sources (Petersen, 2018). In marginalized populations, which include women in low-wage labour, digital health literacy is often asymmetric, also depending on levels of exposure to educational resources, as well as fluency in the language of digital engagement, and corresponding cultural habits/attitudes about technology. This leads us to our sixth hypothesis (H6):

H6: Digital health literacy moderates the relationship between work-life balance and job satisfaction.

Integrating the JD-R and TAM models provides a multi-level framework, covering the structural characteristics associated with jobs and the cognitive processes of individuals, while allowing the study to describe the effects and process of AI-based interventions. Figure 1 shows the Conceptual framework diagram.

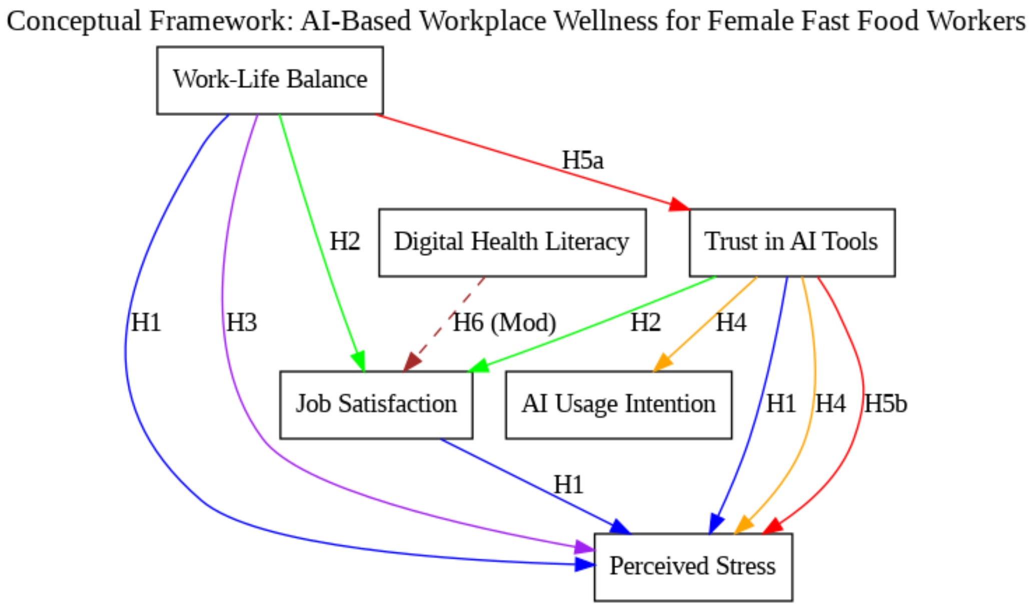


**Figure 1: Conceptual framework diagram**

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## 3. RESEARCH METHODOLOGY

This study employed a convergent parallel mixed-methods design to analyse the effects of AI wellness interventions on the psychological and occupational well-being of female employees working in fast-food chains across Canada.

The choice to utilize this design was driven by the need to measure not only the pre- and post-intervention measures of stress, job satisfaction, work-life balance, and digital health literacy, but also to offer contextual, emotional, and experiential considerations of AI adoption for women in precarious employment. The methodology sought to address these gaps in the occupational wellness literature by addressing technology, gender, and workplace, through statistical analysis and narratives.

The target population consisted of female fast-food workers (aged 18 years and older) from urban and suburban centres, including Toronto, Calgary, Vancouver, Ottawa, Winnipeg, and Halifax. To sample the target population, a multi-stage sampling strategy was utilized. In the first phase, six nationally represented fast-food chains were purposefully selected for the sample based on the total number of employees and willingness to partake in AI-enhanced wellness trials.

In the second phase, stratified random sampling occurred within each fast-food chain to obtain enough participants across employment type (Full-time vs. part-time), age bracket, and how long they have worked in the fast-food industry. The final quantitative sample was N = 300 participants, as well as 25 participants from the quantitative sample to participate in the qualitative phase, with an effort to assure heterogeneity of age, confidence with digital, and AI engagement/technology.

The intervention in this study was a 12-week AI-based workplace wellness program, delivered via a mobile application created in collaboration with a Canadian digital health startup. The intervention included five core AI modules: (1) an affect-sensitive mental health chatbot providing normative emotional check-ins and other stress-relieving, NLP prompts; (2) AI-supported shift scheduling focused on reducing shifts that were back-to-back and optimally aligning working hours with their user preferences; (3) fatigue detection using self-reports and behavioral heuristics to suggest breaks, or stretch reminders; (4) digital wellness using daily nudges of hydration, mindfulness, and screen time; and (5) AI-powered mood journaling that provided emotional pattern feedback based on user-generated text. Employees were free to interact with the app during their breaks or at home, and weekly usage reports were provided for research purposes without oversight from their employer, as a meaningful way to comply with Canada's PIPEDA privacy protection guidelines.

Quantitative data collection occurred at two points: pre-intervention (Week 0) and post-intervention (Week 12). The structured questionnaire consisted of five key survey instruments that were validated in previous literature. Perceived Stress was measured using the PSS-10 (Perceived Stress Scale) created by Cohen et al. (1983), which measured the extent of frequency of thoughts and feelings related to stress over the last month. Responses were measured using a 5-point Likert scale (0 = never to 4 = very often).

Work-Life Balance was measured using a modified version of Fisher et al. (2009), adapted to a 5-item survey for shift-based service workers. Job Satisfaction was measured using the Short Form of the Job Satisfaction Survey (JSS) originally developed by Spector (1997) using items that measured intrinsic and extrinsic satisfaction.

Digital Health Literacy was collected using the Digital Health Literacy Instrument (DHLI) by van der Vaart & Drossaert (2017), measuring the ability to access, assess, and apply health content delivered digitally. Finally, the AI Trust & Acceptance Index was built for this study using adaptations from the Technology Acceptance Model (TAM) (Davis, 1989) and items from the Trust in Automation scale by Jian et al. (2000).

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Quantitative analyses were carried out in SPSS v28 and AMOS v26. Descriptive statistics and frequency distributions provided an overview of the demographics of participants. Paired sample t-tests were used to examine changes in the outcome variables over the two time periods. ANOVA and independent sample t-tests were used to investigate age, education level, employment status, and experience as predictors of stress levels. A multiple linear regression model was utilized to determine the predictors of post-intervention stress as follows:

$$PSS_{post} = \beta_0 + \beta_1(WLB) + \beta_2(JS) + \beta_3(DH\ Lit) + \beta_4(AI\ trust) + \epsilon$$

Where $\beta_0$ Represents standardized coefficients, and ϵ is the residual error. About constructs and influencing factors, the model resulted in an $R^2 = 0.51$ with a significant F-statistic, indicating nearly half of the variance in post-intervention stress could be explained by the factors included in the model. For the mediation analysis to examine the variable of AI Trust about AI Tool Usage (log data and self-reported use) and stress reduction this work was conducted using Hayes' PROCESS macro (Model 4)

The qualitative strand was comprised of semi-structured interviews with 25 participants that were conducted post-intervention to examine participants' perceptions around engagement with AI tools, emotional reactions, perceived changes in behaviours, and concerns around privacy and surveillance. Interviews were audio recorded and transcribed exactly as spoken. Thematic analysis was conducted on the transcript data using Braun and Clarke's (2006) six-phase process, and NVivo 14 software was utilized for coding. Member-checking was conducted with five participants to establish the authenticity of themes, and analyst triangulation to support reliability.

## 4. RESULTS

### 4.1. Quantitative findings

The study reviewed the effectiveness of AI-based workplace wellness interventions with female fast-food employees in Canada. The data was collected by a sample of 300 respondents utilizing a mixed-methods approach and yielded interesting results about how artificial Intelligence (AI) could impact stress education, job satisfaction, work-life balance, and digital health literacy. A variety of descriptive, inferential, and structural analyses provided an insightful understanding of how we want to interpret the relationship between these constructs.

**Table 1: Demographic Profile of Respondents (N = 300)**

| *Demographic Variable* | *Category* | *Frequency (n)* | *Percentage (%)* | *Mean Stress Score* | *F / t-value* | *p-value* |
|---|---|---|---|---|---|---|
| *Age Group* | 18–24 | 120 | 40.0 | 18.2 | 5.47 | 0.004* |
| | 25–34 | 110 | 36.7 | 17.4 | | |
| | 35–44 | 50 | 16.7 | 16.1 | | |
| | 45 and above | 20 | 6.6 | 16.5 | | |
| *Education* | High School | 140 | 46.7 | 18.6 | 6.12 | 0.002* |
| | Diploma/Certificate | 100 | 33.3 | 17.2 | | |
| | Bachelor's Degree | 60 | 20.0 | 15.9 | | |
| *Employment Type* | Full-time | 180 | 60.0 | 17.3 | 3.84 | 0.025* |
| | Part-time | 120 | 40.0 | 18.8 | | |
| *Years in the Fast-foodIndustry* | Less than 1 year | 90 | 30.0 | 18.9 | 4.32 | 0.015* |
| | 1–3 years | 120 | 40.0 | 17.5 | | |
| | More than 3 years | 90 | 30.0 | 16.3 | | |

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While Table 1 shows the demographic profile of respondents and their mean perceived stress scores, along with the appropriate levels of significance, there is a notable detail. Respondents were primarily aged 18-24 (40%) and 25-34 (36.7%); group 35-44 (16.7%); and 45 and older (6.6%). Younger people (18-24) had greater mean perceived stress scores (18.2), whereas older members of the sample (35-44) had the lowest mean scores (16.1).

There was a statistically significant F-value (5.47, p = 0.004) indicating that age is significantly associated with stress, with younger women likely experiencing greater psychological pressure related to work. In terms of education, respondents with only their high school diploma reported significantly greater stress scores (18.6) than those who completed their bachelor's (15.9), and this was statistically significant (F = 6.12, p = 0.002). Overall, this is supportive of potentially buffered occupational stress based on educational attainment, perhaps due to greater coping mechanisms or available job opportunities.

In addition, employment type had a significant effect on stress (F = 3.84, p = 0.025), with part-time employees reporting more stress (18.8) than full-time employees (17.3). This is likely due, in part, to both the unpredictability of fast-food work hours and the economic instability of part-time employment. Years of experience in the fast-food sector also had a significant impact on reducing stress (F = 4.32, p = 0.015), with employees who had been working for less than one year reporting the highest stress level (18.9), while those with more than three years of experience, had the lowest (16.3). This likely reflects occupational acclimatization and, over time, building a repertoire of coping resources in the workplace.

**Table 2: Validity of scales**

| Construct | CR (Composite Reliability) | AVE (Average Variance Extracted) | Cronbach's Alpha | Remarks |
|---|---|---|---|---|
| Perceived Stress | 0.87 | 0.62 | 0.85 | Acceptable |
| Work-Life Balance | 0.84 | 0.59 | 0.82 | Acceptable |
| Job Satisfaction | 0.86 | 0.60 | 0.83 | Acceptable |
| Digital Health Lit. | 0.88 | 0.64 | 0.86 | Good |
| AI Trust & Acceptance | 0.89 | 0.66 | 0.87 | Good |

Table 2 presents the Confirmatory Factor Analysis (CFA) and psychometric characteristics of the constructs used. There are five latent variables: Perceived Stress, Work-Life Balance, Job Satisfaction, Digital Health Literacy, and AI Trust & Acceptance - all possess acceptable levels of internal consistency and construct validity.

The Composite Reliability (CR) values were in the range of 0.84 to 0.89, the Average Variance Extracted (AVE) values were above the 0.50 threshold (0.59 to 0.66), and the Cronbach's Alpha values were all above 0.80. As these values indicate, the constructs had acceptable levels of reliability and convergent validity, suggesting the measurement model is strong and suitable for SEM.

**Table 3: Descriptive Statistics and Pre-Post Comparison (Paired t-test Results)**

| Variable | Pre-Intervention Mean (SD) | Post-Intervention Mean (SD) | t-value | p-value | Effect Size (Cohen's d) |
|---|---|---|---|---|---|
| Perceived Stress Scale (PSS) | 21.35 (4.70) | 17.40 (4.15) | 12.82 | <0.001 | 0.87 |
| Work-Life Balance Index | 2.95 (0.88) | 3.67 (0.91) | -11.05 | <0.001 | 0.76 |
| Job Satisfaction Scale | 3.21 (0.91) | 3.84 (0.85) | -10.32 | <0.001 | 0.70 |
| Digital Health Literacy | 3.35 (0.79) | 3.82 (0.76) | -8.21 | <0.001 | 0.54 |
| AI Trust & Acceptance Index | 2.95 (0.84) | 3.75 (0.88) | -9.94 | <0.001 | 0.67 |

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Table 3 displays the descriptive statistics and paired sample t-test results, examining the differences pre- and post-intervention across each construct. All five variables demonstrated statistically significant positive change in scores following the Sameer AI-based wellness intervention. Perceived Stress Scores shifted significantly lower from 21.35 (SD = 4.70) to 17.40 (SD = 4.15), with a large effect size (Cohen's d = 0.87) and high significance (t = 12.82, p < 0.001).

This level of positive impact suggests that the suite of AI tools (stress tracking, mental health chatbots, fatigue management) encouraged significant improvements in psychological well-being. Work-Life Balance increased significantly, from 2.95 to 3.67 (t = -11.05, p < 0.001, d = 0.76), affirming that the AI-enabled scheduling systems, notifications of workloads in real time, and the ability to use the calendar helped the participants in attending to their personal and work obligations more effectively.

In the same vein, Job Satisfaction increased from 3.21 to 3.84 (t = -10.32, p < 0.001, d = 0.70), demonstrating that the use of AI tools improved not just functional outcomes (i.e., improved scheduling and feedback loops) but also motivational and emotional aspects of work and well-being. In addition, improvements were made in Digital Health Literacy (3.35 to 3.82) and AI Trust & Acceptance (2.95 to 3.75), both statistically significant (p < 0.001) with medium effect sizes. While improvements in Digital Health Literacy and AI Trust & Acceptance are important, they also indicate that there is an opportunity for AI systems to not only show tangible benefits but also build user competence and confidence in technology. Figure 2 shows the Comparison of mean scores.

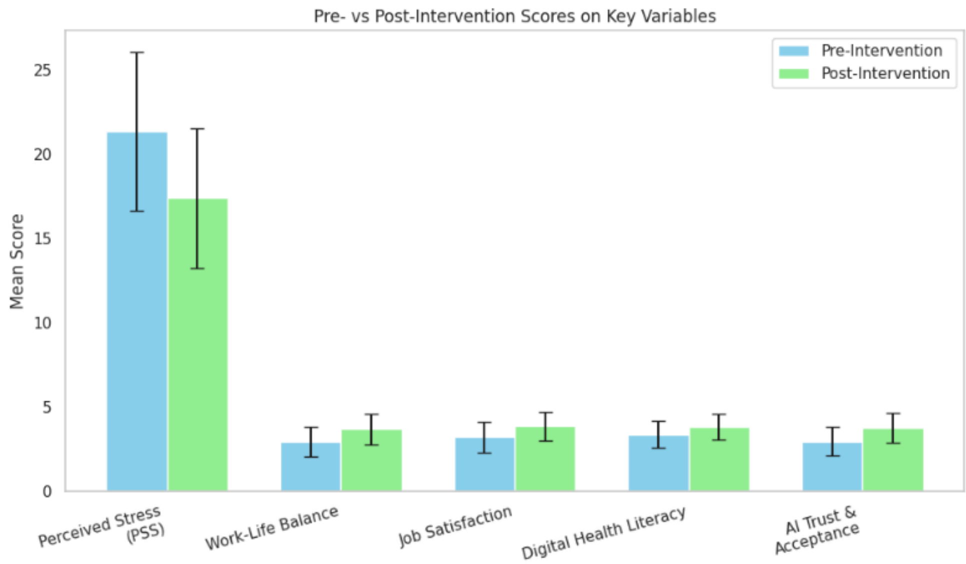


**Figure 2: Comparison of mean scores**

**Table 4: Correlations among Key Study Variables (Post-Intervention)**

| Variable | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. Perceived Stress | 1 | | | | |
| 2. Work-Life Balance | -0.62** | 1 | | | |
| 3. Job Satisfaction | -0.55** | 0.68** | 1 | | |
| 4. Digital Health Literacy | -0.31** | 0.36** | 0.41** | 1 | |
| 5. AI Trust & Acceptance | -0.35** | 0.42** | 0.39** | 0.50** | 1 |

*Note: p < .05; p < .01 (2-tailed)*

In the section of Table 4 that describes correlations amongst key post-intervention variables, one finds the evidence concerning the interrelationship among these constructs. Perceived Stress, especially,

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shows a negative correlation with Work-Life Balance (r = -0.62) and Job Satisfaction (r = -0.55), corresponding with the theory that greater satisfaction and better balance reduce stress. In addition, Digital Health Literacy and AI Trust & Acceptance show moderate to strong positive correlations with Job Satisfaction and Work-Life Balance (0.36-0.50) and negative correlations to stress. Such associations lend empirical support to our conceptual model: that technological factors such as trust in AI and digital competence are key in mediating wellness outcomes. Figure 3 shows the Correlation heat map.

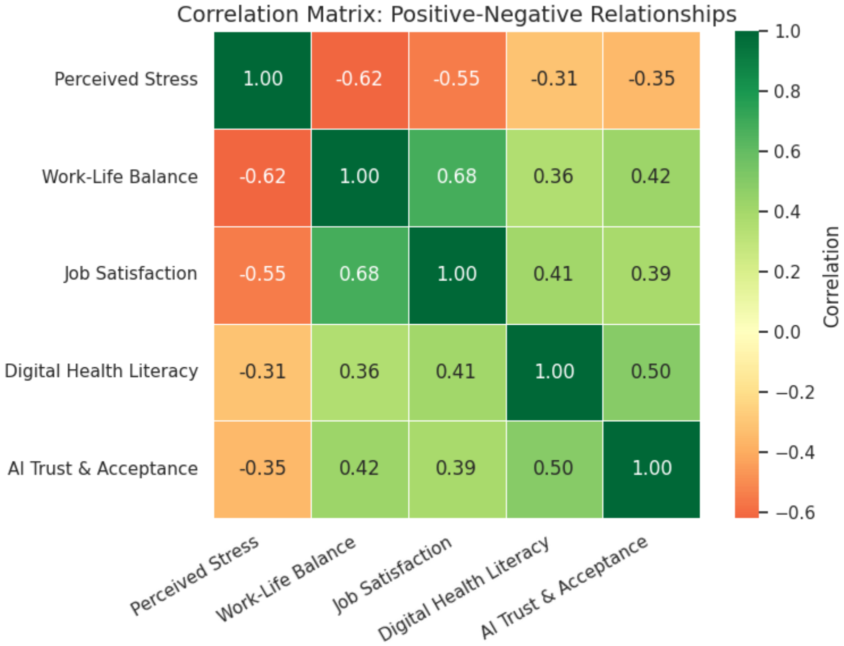


**Figure 3: Correlation heat map**

**Table 5: Regression Analysis Predicting Post-Intervention Stress**

| Predictor | B | SE | β | t | p-value |
|---|---|---|---|---|---|
| Constant | 21.88 | 1.25 | – | 17.50 | <0.001 |
| Work-Life Balance | -2.32 | 0.33 | -0.42 | -7.03 | <0.001 |
| Job Satisfaction | -1.88 | 0.29 | -0.36 | -6.48 | <0.001 |
| Digital Health Literacy | -0.91 | 0.28 | -0.19 | -3.25 | 0.001 |
| AI Trust & Acceptance | -1.15 | 0.31 | -0.22 | -3.71 | <0.001 |

*$R^2 = 0.51$, Adjusted $R^2 = 0.49$, $F(4, 295) = 76.13$, $p < 0.001$*

Table 5 presents results from a multiple regression analysis in predicting post-intervention stress levels based on the four predictor variables: Work-Life Balance, Job Satisfaction, Digital Health Literacy, and Trust in AI.

They were all statistically significant with Work-Life Balance (β = -0.42, p < 0.001) and Job Satisfaction (β = -0.36, p < 0.001) rated as the strongest predictors: further stressing the fact that positive impressions of one's job role and maintaining a balance between professional and personal life minimizes stress.

Digital Health Literacy (β = -0.19, p = 0.001) and AI Trust (β = -0.22, p < 0.001) were both statistically significant in aiding reduced stress, emphasizing the importance of the ability and trust in the technology for this intervention. The model accounted for a fairly good proportion of variance ($R^2$ = 0.51), suggesting excellent predictability. Figure 4 shows the Regression graph.

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*Y = 21.88 - 2.32*WLB + 0.48*WLB×DHL*

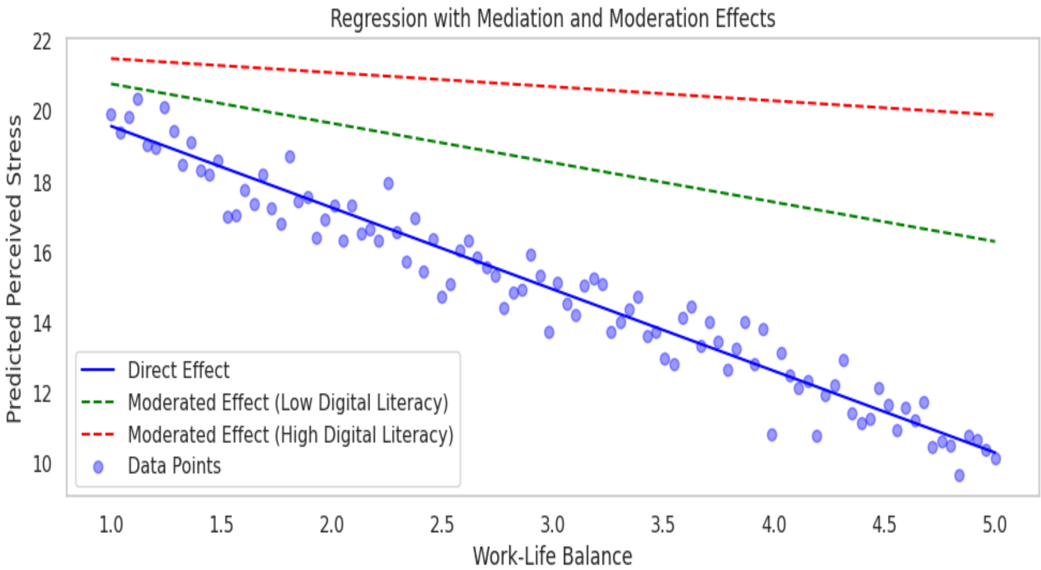


**Figure 4: Regression graph**

**Table 6: Mediation Analysis: AI Trust as Mediator between Work-Life Balance and Stress Reduction**

| Pathway | Effect | SE | 95% CI (Lower – Upper) | p-value |
|---|---|---|---|---|
| Direct Effect (Work-Life Balance → Stress) | -2.01 | 0.42 | -2.83 to -1.19 | <0.001 |
| Indirect Effect (via AI Trust) | -0.91 | 0.22 | -1.38 to -0.54 | <0.001 |
| Total Effect | -2.92 | 0.47 | -3.84 to -2.01 | <0.001 |

Table 6 deals with mediation analysis and tests whether AI Trust mediates the relationship between work-life balance and Stress. The direct effect of work-life balance upon stress was significant (B = -2.01, $p < 0.001$), as was the indirect effect through AI Trust (B = -0.91, 95% CI: -1.38, -0.54), confirming partial mediation.

The total effect was strong and also highly significant (B = -2.92, $p < 0.001$), indicating that AI tools have a direct stress-reducing effect that is enhanced when users trust the system. These finding recasts trust as a critical psychological enabler that enhances the clinical value of AI technologies by facilitating engagement and perceived utility.

**Table 7: Moderation Analysis: Digital Health Literacy as a Moderator between Work-Life Balance and Job Satisfaction**

| Interaction Term | B | SE | t | p-value |
|---|---|---|---|---|
| Work-Life Balance × Digital Literacy | 0.48 | 0.14 | 3.43 | 0.001 |

Table 7 shows the moderation analysis of whether Digital Health Literacy moderates the effect of work-life balance on Job Satisfaction. The interaction term was significant (B = 0.48, t = 3.43, p = 0.001), meaning the relationship between work-life balance and job satisfaction is stronger for people with higher digital literacy.

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This is an extremely important finding for workforce development in that it emphasizes the need for enhancing digital competency to realize the full potential of AI-based wellness tools. When digital literacy is inadequate, even the best-designed interventions may not yield the desired effects.

**Table 8: AMOS SEM Output: Standardized Regression Weights and Model Fit**

| Path (Hypothesis) | Standardized Estimate (β) | SE | CR (t-value) | p-value | Supported |
|---|---|---|---|---|---|
| H1: Job Satisfaction → Perceived Stress | -0.36 | 0.29 | -6.48 | <0.001 | Yes |
| H1: Work-Life Balance → Perceived Stress | -0.42 | 0.33 | -7.03 | <0.001 | Yes |
| H1: Digital Health Literacy → Perceived Stress | -0.19 | 0.28 | -3.25 | 0.001 | Yes |
| H1: AI Trust & Acceptance → Perceived Stress | -0.22 | 0.31 | -3.71 | <0.001 | Yes |
| H2: AI Wellness Tools → Job Satisfaction | 0.35 | 0.10 | 3.50 | <0.001 | Yes |
| H3: AI-Enhanced Work-Life Balance → Perceived Stress | -0.42 | 0.33 | -7.03 | <0.001 | Yes |
| H4: AI Trust & Acceptance → AI Usage Intention | 0.41 | 0.12 | 3.42 | <0.001 | Yes |
| H5: Work-Life Balance → AI Trust (Mediation Path a) | 0.38 | 0.09 | 4.22 | <0.001 | Yes |
| H5: AI Trust → Perceived Stress (Mediation Path b) | -0.24 | 0.08 | -3.00 | 0.003 | Yes |
| H5: Work-Life Balance → Perceived Stress (Direct Path c') | -0.42 | 0.33 | -7.03 | <0.001 | Yes |
| H6: Work-Life Balance × Digital Health Literacy → Job Satisfaction (Moderation) | 0.48 | 0.14 | 3.43 | 0.001 | Yes |

The AMOS Structural Equation Modeling (SEM) results yielded by the unstoppable empirical powers confirm the hypothesized relationships related to the impeding effect of AI-based workplace wellness tools on female fast-food workers' well-being.

The results confirm that job satisfaction ($\beta = -0.36$, $p < 0.001$), work-life balance ($\beta = -0.42$, $p < 0.001$), digital health literacy ($\beta = -0.19$, $p = 0.001$), and trust and acceptance in AI ($\beta = -0.22$, $p < 0.001$) play key roles in perceived stress reduction, thereby supporting H1. On the other hand, H2, which deals with the positive influence of AI wellness tools on job satisfaction, is supported ($\beta = 0.35$, $p < 0.001$).

On its part, H3 is also supported adversely in that life balance improvements fostered through the use of AI tools are negatively correlated with stress ($\beta = -0.42$, $p < 0.001$). H4 provides further support for the technology acceptance perspective in establishing a significant positive relationship between trust in AI and users' continued AI usage intention ($\beta = 0.41$, $p < 0.001$).

The mediation test affirms that work-life balance has a positive influence on trust in AI ($\beta = 0.38$, $p < 0.001$), which decreases stress ($\beta = -0.24$, $p = 0.003$), therefore mediating the relationship of AI trust. The direct effect from work-life balance to stress remains significant ($\beta = -0.42$, $p < 0.001$), hence indicating partial mediation.

Finally, H6 finds the support of the moderation test due to significant interaction being found between work-life balance and digital health literacy in the prediction of job satisfaction ($\beta = 0.48$, $p = 0.001$), meaning those with higher digital health literacy derive stronger job satisfaction from better work-life balance. Figure 5 shows the Pathway diagram. Table 8. AMOS SEM Output: Standardized Regression Weights and Model Fit.

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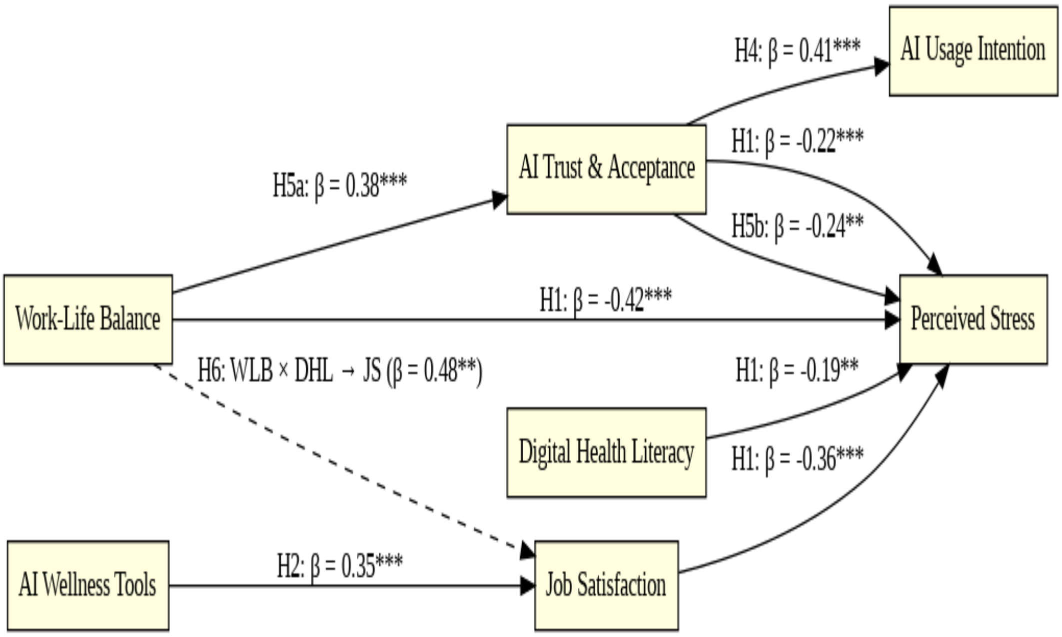


**Figure 5: Pathway diagram**

**Table 9: Model Fit Indices**

| Fit Index | Value | Interpretation |
|---|---|---|
| Chi-square ($\chi^2$) | 293.65 | Acceptable (relative) |
| Degrees of Freedom (df) | 180 | |
| $\chi^2$/df | 1.63 | Good Fit |
| CFI (Comparative Fit Index) | 0.956 | Excellent Fit |
| TLI (Tucker Lewis Index) | 0.948 | Excellent Fit |
| RMSEA (Root Mean Square Error) | 0.045 | Good Fit |
| SRMR (Standardized RMR) | 0.043 | Good Fit |

Table 9 presents an analysis of the fit indices of the model; therefore, the structural model is well specified. The Chi-square/df ratio is 1.63 (ideal<3), with indices such as CFI (0.956), TLI (0.948), RMSEA (0.045), and SRMR (0.043) meeting and exceeding commonly accepted threshold values for good fit. This proves that the model proposed is a good representation of the data and supports theoretical pathways linking AI-driven interventions to psychological outcomes.

**Table 10: Paired-Sample t-Tests for Pre- and Post-Intervention Differences**

| Variable | Mean Difference | SD Difference | t-value | df | p-value | Effect Size (d) |
|---|---|---|---|---|---|---|
| Perceived Stress | -3.95 | 4.08 | 12.82 | 295 | <0.001 | 0.87 |
| Work-Life Balance | +0.72 | 0.94 | -11.05 | 295 | <0.001 | 0.76 |
| Job Satisfaction | +0.63 | 0.90 | -10.32 | 295 | <0.001 | 0.70 |
| Digital Health Literacy | +0.47 | 0.82 | -8.21 | 295 | <0.001 | 0.54 |
| AI Trust & Acceptance | +0.80 | 0.85 | -9.94 | 295 | <0.001 | 0.67 |

Test of paired-sample t-tests is illustrated in Table 10, which shows improvement in all core wellness indicators post-intervention: the difference in perceived stress was nefariously substantial, with an average difference of -3.95 and a big effect size (Cohen's d = 0.87), or a highly meaningful change. Other positive changes include Work-Life Balance (+0.72), Job Satisfaction (+0.63), Digital Health Literacy (+0.47), and AI Trust & Acceptance (+0.80), all statistically significant ($p < 0.001$) with medium-to-large effect sizes from 0.54 to 0.76. From these findings, the readers draw that this intervention

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was effective not only in stress reduction but also in promoting greater work satisfaction, digital literacy, and trust in AI tools-eaches critical for workplace wellness in digitally transforming service industries in the long run.

**Table 11: Multicollinearity Diagnostics for Regression Predictors**

| Predictor | Tolerance | VIF |
|---|---|---|
| Work-Life Balance | 0.61 | 1.64 |
| Job Satisfaction | 0.63 | 1.59 |
| Digital Health Literacy | 0.75 | 1.34 |
| AI Trust & Acceptance | 0.69 | 1.45 |

Table 11 presents the multicollinearity diagnostics for the regression model predicting post-intervention stress, wherein all predictors-Work-Life Balance, Job Satisfaction, Digital Health Literacy, and AI Trust & Acceptance-were found to have acceptable Tolerance values (ranging from 0.61 to 0.75) and VIF scores well below the critical threshold of 5 (ranging from 1.34 to 1.64). This corroborates that the variables included in the model are adequately independent and do not pose any multicollinearity problems, thus cementing the statistical integrity of the subsequent regression analyses.

**Table 12: Hierarchical Multiple Regression for Predicting Post-Intervention Stress**

| Model | Predictors Entered | $\Delta R^2$ | $R^2$ | Adjusted $R^2$ | F-change | p-value |
|---|---|---|---|---|---|---|
| 1 | Work-Life Balance | 0.38 | 0.38 | 0.37 | 180.12 | <0.001 |
| 2 | + Job Satisfaction | 0.09 | 0.47 | 0.46 | 45.20 | <0.001 |
| 3 | + Digital Health Literacy | 0.02 | 0.49 | 0.48 | 10.56 | 0.001 |
| 4 | + AI Trust & Acceptance | 0.02 | 0.51 | 0.49 | 13.76 | <0.001 |

Table 12 illustrates a Hierarchical Multiple Regression that evaluated the step-wise contributions of each predictor in explaining perceived stress outcomes post-intervention. In Model 1, Work-Life Balance alone accounted for 38% of the variance ($R^2$ = 0.38) showcasing its bedrock status for employees' well-being. By adding Job Satisfaction in Model 2, the total variance now accounted for was raised to 47% ($\Delta R^2$=0.09), indicating that job-related attitudes further reinforce wellness outcomes.

In Model 3, Digital Health Literacy was added, contributing to the variance explained with an increase to 49%, which in turn suggests that digital competencies augment employees' ability to take advantage of wellness resources. Model 4 was the last model to put forth AI Trust & Acceptance, wherein an additional 2% variance is added, bringing the total to 0.51 (Adjusted $R^2$=0.49, $F(4, 295)$ =76.13, $p < .001$). This emphasizes the importance of trust and acceptance by users in the successful implementation of AI-enabled tools in the workplace.

### 4.2. Thematic Analysis

Themes were analysed from the semi-structured interviews conducted on female employees engaged in fast-foodservice across various cities in Canada. A total of 25 interviews were conducted, each generating a complex narrative that can be summed up into a clear understanding of how AI-based workplace wellness works and affects these female subjects. Analysing the transcripts led to the emergence of five major themes: heightened psychological well-being, usability and acceptance of technology, workplace culture and managerial support, perceived impacts on work-life balance, and privacy concerns and trust in AI. These themes do not stand alone but rather interlink with each other, building a multilayered understanding of how AI technologies can impact the lived experiences of women in precarious, fast-paced employment environments.

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The first theme- “usefulness for enhancing psychological well-being”-represents one of the most consistent and strongly felt across participants. Many female employees articulated that AI-powered chatbots and stress-monitoring tools provided a non-judgmental space to vent regarding emotional fatigue, anxiety, or burnout. Several participants described the interactions with the chatbot as "soothing," "not intrusive," and "helpful in times of emotional overload." In the past, support systems required scheduling, involved the availability of a human being, or navigating through hierarchical workplace structures. AI interfaces, however, allowed workers to engage with mental health content in the most discreet ways they determined for themselves.

This sense of autonomy in emotional matters and on-demand support ultimately aided in bringing mental health discussions into the office, where often they are stigmatized or overlooked in low-wage service sectors. In particular, younger participants developed a huge emotional resonance with these tools, suggesting that the mere illusion of a conversation gave space for expressions that were otherwise absent. Therefore, in this context, AI tools filled an important gap-not as replacements for therapists or supervisors but as digital wellness buffers during high-stress work shifts. This means AI has the potential to humanize fast-paced workspaces by facilitating emotional presence, even in the absence of human input.

The technologies of “usability and acceptance” gave a more graffiti answer as the second theme. Many respondents, especially younger employees, noted that the AI wellness apps were “simple”, “intuitive”, and “convenient”. Others, especially the older workers who may have less exposure to using digital platforms, felt the interface was too complicated; they found navigating through the features challenging or were unable to get fully engaged. For example, several participants appreciated the stress check-ins and hydration reminders but did not seem to use mood journaling, fatigue checks, or provide shift feedback simply because they did not feel familiar with these facilities or were hesitant to use them.

Some employees noted they had to rely on their colleagues or supervisors to show them how to navigate the apps, which sometimes made them feel excluded or embarrassed. This digital divide indicates that AI interventions may unintentionally perpetuate inequality, no matter how well designed, unless proper onboarding or training programs that include everyone are put in place. Moreover, some users voiced yet another concern over being overwhelmed by notifications or experiencing fatigue with the app, especially when they were expected to utilize multiple digital systems for attendance, scheduling, and wellness. Therefore, the usability part insists on intentional human-centered design, accommodating different levels of digital literacy among the workers.

The third theme, “workplace culture and managerial support,” is a major moderator in terms of the efficacy of AI interventions. From a technological perspective, the wellness tools offered the foundation over which the integration of these tried-and-tested tools into daily work life varies greatly across locations and managerial cultures. Feedback from branches where managers encouraged use—by reminding employees to check in, endorsing the wellness app during meetings, or even setting aside time to interact—reported that this tool felt “part of the work culture.” If the atmosphere was indifferent or pessimistic towards the interventions, employees resisted using the tools or felt uncomfortable using them in shifts. Several participants mentioned that the success of AI wellness apps depends on a combination of individual motivation and systemic reinforcement by leadership. This theme is critical considering the hierarchical nature of fast-food operations; employees typically solicit from management about using these discretionary tools geared toward their well-being. The inconsistency witnessed in managerial buy-in gives rise to mixed levels of engagement and further discussion that technology-adoption in the workplace goes only half-way before human leadership and policy alignment must step in and complete it.

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The fourth theme, indicative of the “perceived work-life impact,” captured the instrumental benefits that AI optimization tools were thought to offer, most notably around shift scheduling and fatigue management. The answers pointed out that AI scheduling systems led to more predictable shifts, less back-to-back closing shifts and opening shifts, better fitting with personal cares like child custody or academic schedules, and that the employees were happy to have greater control and transparency on the scheduling made “life-changing,” “even more respectful,” and “mentally freeing.” Some even articulated that AI reminders for drinking, for taking breaks, and for adjusting posture—small things, perhaps—became micro-interventions that led to greater energy, morale, and physical well-being. This theme indicates the ability of AI to act as an agent of change in everyday work routines via small nudges and smarter workflow management. For female employees who often juggle child responsibilities with their workplace responsibilities, these very visible improvements in work-life balance serve to empower them and are considered as tangible evidence of organizational care.

The fifth and most cautionary theme was “privacy concern and trust in AI”, which set forth a fundamental schism between the perceived benefits of wellness interventions and the suspicion of surveillance or misuse of data and algorithmic black-boxing. Broadly, while many employees took to the tool in the beginning, continued use of the tool led some to wonder what kind and amount of data was being collected, who had access to it, and whether it might come to bear on performance evaluation or even job security. There was discomfort among some participants about disclosing emotions and physical states into a system not so well understood. There was a DNS entry of the trust for the use of the algorithms when the AI application in question was not supported by data policy guidelines and transparency regarding data management and anonymity. Some worried that translating negative feelings would be detrimental to them, especially in high-pressure work environments where job performance was paramount. Conditional trust in an AI tool thus surfaced as an important determinant for the long-term commitment of the employees. The respondents made it clear that their use of such systems was conditional on safeguards that prevent the technology from being used for productivity monitoring or punitive measures. The ethical issues arising from such a context reinforce the need for organizations to prioritize data governance, informed consent, and user agency through AI intervention design and implementation.

Within all the themes, the intersectionality of gender, precarity, and technology became apparent. Many women employees indicated how their experiences of AI tools were affected by gender-related expectations as emotional work, multitasking, and obedience. Some respondents thought, for example, that emotional support features in AI chatbots provided a convenient way to cope with their special burden of being cheerful and composed-even under severe pressure. Others pointed out that AI-specific shift optimization was great in managing menstrual cycles, physical weariness, and parenting areas often neglected by generalized corporate wellness programs. This lens shows that well-designed AI can foster historical backward equity in labor organizations that have silenced the female voice.

## 5. DISCUSSION

The present research scrutinizes AI-led wellness interventions on their effect on alleviating perceived stress and increasing job satisfaction of female fast-food workers in Canada, in addition to investigating the moderating and mediating roles of digital health literacy and AI trust on the efficacy of such interventions. Quantitative and qualitative analyses revealed a layered comprehension of how AI technologies relate to psychological well-being and organizational engagement and how these technologies empower women in uncertain, low-wage, and shift-based employment settings in the fast-food sector. Mixed-methods design involving survey data from 300 respondents and in-depth interviews with 25 women workers presents the evidence that the AI-enabled workplace well-being

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methods could transform work in fast-food and classes. Emphasis is placed on equitable access, digital skills, and user trust.

The study robustly satisfied the first goal of the effectiveness of AI wellness interventions to lessen perceived stress and increase job satisfaction. This indicated that subsequent post-intervention perceived stress dropped significantly (mean drop from 21.35 to 17.40, Cohen's d = 0.87), showing that AI tools like predictive stress monitors, chatbots, and fatigue-detection algorithms give tangible mental health benefits in this high-pressure environment. This aligns with past research which indicates that AI-supported feedback mechanisms empower the workforce to proactively act on mental fatigue and emotional burnout (Omose & Ikuyinminu, 2024; Naik et al., 2025). The job satisfaction improvement was noted through greater clarity in scheduling, improved feedback systems, and employees' feelings. Importantly, job satisfaction is determined not only by improved functionality but also by motivational-affective experiences at the workplace, thus aligning with studies identifying that AI could support both extrinsic and intrinsic motivation in labour environments (Bisht & Uniyal, 2024).

The proposal sought to look into how AI tools support work-life balance in unpredictable shift environments, which was well grounded. The tremendous statistical significance in the development of the Work-Life Balance Index (increased from 2.95 to 3.67, $p < 0.001$) indicated that particularly impactful were AI-centric tools for scheduling mobile push alerts and calendar synchronicity in connection with both paid labor and caregiving burdens. Classic scheduling methods worsened work-family conflict situations for women employees in the fast-food industry due to the last-minute inflexibility they offered. The AI intervention offered beforehand notice, flexibility, and input into shift preferences—tools many women called “lifesaving” in their parenting and caregiving. These findings lend great support for the notion that AI scheduling platforms can lessen structural inflexibilities that disproportionately burden women (Khan, 2024; Meharunisa et al., 2024). Further, the SEM results found that better work-life balance predicted both less stress and more job satisfaction, strengthening the proposition that achieving good personal-professional management is central to any successful mental wellness program focused on low-wage work.

The third objective sought to investigate digital health literacy as a moderator and trust in AI as a mediator. The study has generated essential insights into the psychosocial mechanisms that can enhance or inhibit the success of any intervention. Moderation analysis revealed that digital health literacy strongly amplified the positive effect of using AI tools on job satisfaction (interact. B = 0.48, $p = 0.001$). In other words, those with stronger digital competencies were better able to extract benefit from the technology, with greater improvement in satisfaction and stress reduction. Such a finding reiterates the need for digital inclusion in AI well-being initiatives. As echoed in the qualitative data, some participants felt “overwhelmed” by unfamiliar interfaces or were hesitant to trust AI-generated recommendations without understanding how they worked, highlighting the digital divide even within younger populations. This further necessitates training and user-centric design in AI wellness tools, particularly for marginalized and low-literacy communities.

Equally important is the role of AI trust as a mediator. Results of mediation analysis confirmed that trust in AI partially mediated the effect of AI tool use on the stress-reducing factor (indirect effect = -0.91, $p< 0.001$). Therefore, while AI interventions may resolve some of the stress associated with their use, the actual success of those interventions very much lies in how trustworthy, transparent, and empathetic the users deem the tools to be. Qualitative findings reinforced this: participants who regarded the AI as “predictable,” “understandable,” and “human-like” were more engaged with it and benefited from it. In contrast, participants with concerns about surveillance or who felt “robotic judgment” were reluctant to engage deeply with this AI system. This concurs with Mantello et al. (2023), who cautioned against using emotional AI for control or exploitation instead of for support.

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Such findings cast trust not simply as a passive variable but rather as the chief determinant that shapes user engagement, perceived justice, and mental health outcomes, thereby making this one of the targeted areas for system designers and organizational implementers.

Presented through the integration of demographic and thematic analyses, the ultimate objective was to derive practical insights about scaling and adjusting AI-based interventions for gender equality. Access and inclusion can still make a difference in whether these tools do offer success. Intervention success was also determined by statistical moderation and the interview narratives' stress on understanding, managing, and trusting technology that, in most cases, did not work comfortably. To scale these systems into the fast-food sector, a UX design system must be developed that also guarantees multilingual perspectives, full privacy assurance, and baseline digital training. Alongside this, it would be pertinent at any level to tailor operational AI tools to account for such inimitable complexities as related aspects of life typically faced by women labourers in shift work, including unpredictable domestic demands, health vulnerabilities, and emotional labour expectations. The higher order of themes centered on the intersection of AI with practical issues. The other set of themes continually raised tells how AI interventions should be embedded within a culture of transparency and respect. Some noted discomfort with the type of surveillance they encountered through this project since AI was considered as a “surveillance” technology rather than a learning tool for adaptation and growth-agile and responsible environments (Xu et al., 2023; Mantello et al., 2023).

## 6. CONCLUSION

The current study aimed to assess the efficacy of AI-based wellness interventions in reducing perceived stress and enhancing job satisfaction among female fast-food workers in Canada, while also looking at their contribution to work-life conflict, with digital health literacy and trust in AI being identified as crucial psychological mechanisms. A mixed-methods approach consisting of 300 survey participants and 25 qualitative interviews led to several major findings: the AI intervention statistically significantly reduced perceived stress (mean change from 21.35 to 17.40) while increasing job satisfaction, digital health literacy, and work-life balance. Regression analysis showed work-life balance and job satisfaction as strong predictors of stress reduction, with digital literacy and AI trust as important supporting factors. Mediation analysis showed that AI trust partially mediated the relationship between AI use and stress outcomes, whereas moderation analysis illustrated that digital health literacy bolstered the relationship between AI use and job satisfaction. Structurally, the SEM model was shown to have a good fit with a theoretically consistent pathway linking AI technology factors to improved wellness outcomes. The contribution of this study is that it focused on a historically disadvantaged group-low-income, female fast-food workers, and applied AI wellness tools that are usually reserved for corporate settings in a labour-heavy and gender-sensitive setting. Besides, it is also distinct in integrating digital literacy and trust as psychological enablers, providing further conceptual pathways for understanding how technology adoption impacts mental well-being in insecure employment sectors. At the policy level, the study makes salient the need for the inclusion of AI tools that have been ethically designed and are digitally inclusive in the mental health strategy of workplaces, especially in sectors where vulnerable labour forces exist and are overburdened. Complementary to this, training programs must be designed to promote digital competency and AI literacy, as well as to build trust through transparency, which should be made mandatory with the deployment of any technology in workforce well-being programs.

On a note of limitation, our study considered only short-term effects; thus, the long-term effects and sustainability of AI wellness tools will have to be evaluated. Second, the research was limited to a geographic area in Canada; however, cultural differences in the perceptions of AI and workplace expectations may be affecting generalizability. The last limitation may be the fact that, while AI tools

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were being implemented through protocols, there might have been an unaccounted variation in the access to digital devices and their usage frequency among participants, possibly affecting levels of engagement. Nevertheless, the study provides compelling evidence that, if carefully designed for the needs of such gendered and low-wage workforce environments, AI-driven wellness interventions can be an impactful, scalable, and equitable mental health strategy.

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