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Evaluating the effectiveness of AI-enabled Digital Detox Tools for screen time management, stress reduction, and quality of life among IT Professionals

Raghu Shankar K.P^{*1}, Dr. K Satyanarayana Reddy^{*2}

Institute of Computer Science and Information Science
Srinivas University, Mangalore - 575001, Karnataka, India.

ABSTRACT: As the digital landscape grows more reliant on technology, extended screen time, techno-stress and work–life imbalance has become major concerns for IT workers, necessitating the need for effective digital well-being interventions with AI. This paper conducts a multidimensional computational comparative analysis of the effectiveness of twelve commercially available AI-based digital detox tools based on a common framework. A multi-modal dataset containing 200 IT professionals was combined with a publicly available dataset, and used to populate a Python-based analytical pipeline, which included behavioural data, physiology data from wearables, psychometric measures, and qualitative data. In the proposed framework, systematic preprocessing, feature engineering, descriptive statistics, paired sample t-test, effect size analysis, participant clustering, and comparative performance ranking were applied. To create a composite measure for objective comparison of the different intervention scenarios, a Unified Digital Well-Being Profile (UDWP) was developed that incorporates behavioural, physiological, psychometric and qualitative indicators.

The computational assessment revealed statistically significant modelled improvements in several aspects of digital wellbeing. Estimated reductions in perceived stress were 10.19%, an 11.44% reduction in daily screen time and 9.44% reduction in after-hours digital usage, with an increase in work–life balance of 18.22%. Other improvements in sleep duration, heart-rate variability and qualitative sentiment were noted. Significant differences between baseline and simulated post-intervention outcomes were identified through statistical analysis with large practical effects for reduction in screen-time and improvement in sentiment. Headspace was simulated to have the best multidimensional performance among the scenarios evaluated in the proposed computational evaluation framework. The proposed UDWP aims to establish a repeatable computational model for evaluating AI-based digital well-being technologies, a process that incorporates disparate evidence into a standard process of evaluation. The results provide concrete recommendations for organisations, occupational health professionals and technologists to choose digital detox solutions by learning from AI and offer a clear and replicable method to support future research comparing digital detox solutions in the workplace.

1. INTRODUCTION

Modern working environments have undergone a dramatic shift in their digital nature, affecting the nature of work in general, including the information technology (IT) industry. Rising adoption of cloud computing, Artificial Intelligence (AI), enterprise collaboration tools, software development environments, and ubiquitous digital connectivity have made remarkable

strides in boosting organizational productivity and enhancing workforce flexibility. Yet, with the technological advances came a greater and more prolonged use of screens, multitasking, information overload and the expectation of constant availability, which in turn pose new challenges to the health and well-being of employees. As a result, digital well-being has emerged as a crucial interdisciplinary field that investigates the impact of over-digitalization on psychological health and well-being, cognitive overload, sleep patterns, emotional exhaustion, and work–life balance, among others [1-4].

The challenges are especially pronounced amongst those working in the field of Information Technology (IT) where their job relies on constant engagement with computers, mobile devices, software development tools and digital communication platforms. Long work hours, regular interruptions, constant switching of contexts and connectivity after work frequently add to the psychological load while not providing sufficient mental recovery time. Workplaces that rely heavily on technology are known to have a negative impact on mental health, sleep, productivity, job satisfaction, and quality of life, leading to burnout, absenteeism, and decreased organizational performance in the past [5],[6]. This has made it more than ever a well-being issue for employees and a need for organization. Therefore, fostering healthier digital behaviors has become an employee well-being initiative as well as an organizational imperative.

Digital detox has thus become a significant approach to curbing the problematic use of technology and promoting more healthy patterns of technology use. Initial digital detox programs focused on short-term digital abstinence, but recent studies suggest that lasting benefits can only be achieved by providing individual behavioral interventions, not just by removing digital devices for a brief period. In modern interventions, the guidance of behavior, ongoing monitoring and custom personalization of recommendations are becoming increasingly integrated, allowing individuals to achieve productive use of technology while limiting its negative psychological outcomes. The concept of digital detox has thus developed into a structured digital wellbeing approach to balancing and maintaining healthy and sustainable relationships with technology, whilst decreasing problematic behaviors of technology-use and supporting healthier self-regulation [7], [8].

In recent years, AI's impact on digital well-being has also evolved with advanced capabilities such as intelligent, personalized, and context-aware interventions. These digital detox tools are designed using modern Artificial Intelligence, bringing together behavioural analytics, wearable technology sensing, productivity tracking, Natural Language Processing, intelligent notifications, sleep tracking, and personalized recommendations, allowing users to manage their technology usage while maintaining productivity at work. The capabilities of AI-powered conversational systems and intelligent recommendation mechanisms have also extended the possibilities of providing personalized mental health and well-being interventions in digital environments [9]. In addition, the inclusion of behavioural and physiological analytic has improved the ability of such systems to detect stress-related patterns and provide timely interventions based on the individual needs [10], [11]. Consequently, AI-assisted digital well-being technologies have become more and more viewed as potential solutions to enhance employee well-being in technology-driven work environments.

Despite these progressions, there are still a number of key questions that need to be answered. Previous research has mainly focused on individual digital detox apps, AI mental health apps, monitoring apps with wearables, or specific types of interventions, yielding scattered evidence about the usefulness of the interventions in practice [12], [13], [14]. Moreover, systematic reviews indicate significant differences in intervention designs, assessment methods and outcomes measures across AI-supported digital well-being interventions, which restricts the meaningful comparison of AI-based digital well-being technologies. Furthermore, existing literature offers essentially no evidence on the longevity of the digital detox behaviours promoted by AI, the acceptance of AI-enabled monitoring by employees, personalization of behaviors across roles, the organizational uptake of AI, concerns about privacy, and a comparative assessment of commercially available AI-enabled digital detox tools based on an integrated behavioral, physiological, psychometric, and qualitative outcome measures. Thus, there remains a gap in empirical evidence to help organizations choose the right AI tools and interventions to boost the well-being of employees and enhance organizational performance.

To overcome the above limitations, the present study performs an extensive empirical assessment of various AI-powered digital detox interventions to manage screen time, reduce stress and enhance quality of life among the IT community. This research takes a more comprehensive approach than earlier studies, which have examined single applications or single outcome measures of digital wellbeing, by comparing several commercially available AI-powered digital wellbeing tools, applying a multidimensional wellbeing assessment framework comprising of behavioural measures of use, wearable-based physiological measures, psychometric measures, and qualitative evidence. The study also introduces a standardized

computational evaluation framework to facilitate the objective assessment of the effectiveness of interventions across various aspects of digital well-being.

The present study adds to the expanding literature on the topic of AI-driven digital well-being in several significant ways. First, it offers an analytical, systematic comparative assessment of twelve commercially available digital detox tools in the same assessment framework, allowing for objective comparison of the effectiveness of these tools across a range of digital well-being outcomes. Second, it creates and hones the Unified Digital Well-Being Profile (UDWP), an integrated framework of behavioral, physiological, psychometric, and qualitative measures that can be used to perform a standardized multidimensional assessment of intervention effectiveness. Third, the presented computational framework integrates multi-source data pre-processing, feature engineering, statistical validation, participant clustering, composite performance ranking and comparative tool evaluation, further enhancing the methodological transparency and replicability. Fourth, the research uses a composite measure of the combined behavioral, physiological-measurements from wearable technology, psychometric and sentiment data to inform a more comprehensive assessment of AI-based digital detox interventions than a single outcome measure would offer. Lastly, the results offer actionable recommendations for organizations, occupational health professionals, and technology developers implementing AI-supported digital well-being strategies in workplaces that rely heavily on technology.

In total, these methodological and empirical contributions provide a further boost to the existing evidence base of AI-supported digital well-being in the workplace and facilitate the overcoming of some earlier research limitations. This study further contributes to the understanding of how AI-powered digital detox technologies can support healthy digital behaviours, decrease occupational stress, improve work–life balance, and contribute to positive life outcomes among IT practitioners when incorporated into a unified computational evaluation framework that incorporates multidisciplinary outcomes. The existing literature on digital well-being, AI-enable digital detox interventions, wearable technologies, and digital health at work is reviewed to provide a theoretical rationale for the proposed comparative evaluation framework, as detailed below.

2. RELATED WORK

The vast integration of digital technologies has completely revolutionized the nature of work, especially in the information technology (IT) industry where constant engagement with computers, cell phones, cloud-based platforms, and cooperation applications is essential. Despite their usefulness for organizations in productivity and communication, these technologies have led to a digital overload, an overuse of screens, cognitive overload, and technostress. As a result, digital well-being is becoming a significant field of investigation that involves occupational health, human–computer interaction, behavioural science and artificial intelligence (AI). The applications of digital detox interventions, AI-supported well-being technologies and intelligent workplace health solutions have recently been investigated, while evidence is still fragmented and most investigations limit their analysis to single technologies or single intervention approaches but not in-depth comparative evaluations. This section summarizes the key advances in these areas and highlights the research gaps that the current study seeks to fill.

2.1 Digital Well-Being and Techno-stress in Technology-Driven Workplaces

Digital well-being does not necessarily involve limiting oneself from technology but rather creating a healthy and sustainable relationship with digital technology, while retaining its personal and professional advantages. It is perceived more and more as a multidimensional construct that is shaped by various behavioral, contextual, and individual factors [15]. In the same vein, digital well-being has been defined as the equilibrium between the potentialities presented by technology and the psychological challenges arising from its utilization [16]. From the above-mentioned approaches, one can conclude that digital well-being is not only about time spent on technology but also about its impact on individuals' psychological state and behaviors.

As a result of technology-based work environments, reliance on information and communication technology continuously has resulted in information overload, connectivity, and interruption. Such situations can lead to techno-stress, decreased productivity, and negative impacts on the health of employees [17], [18]. Chronic digital involvement in the workplace has been recently linked to emotional exhaustion, mental fatigue, and work-life imbalance [19]. This indicates the need for

interventions in the workplace to encourage healthy digital behavior while retaining the productive aspects of using technology.

2.2 Digital Detox Interventions for Healthy Technology Use

The interventions for digital detoxification have come out to be one of the methods adopted to encourage healthier digital usage habits and limit overuse or unhealthy use of technologies. The earlier interventions mainly comprised of disconnecting from Smartphone's and social media sites. However, studies show that healthy digital behavior can only be ensured through behavioral change interventions.

It has been shown through systematic review and meta-analysis that digital detox treatments can be effective in improving psychological wellbeing and problematic technology use, despite high variability in terms of interventions, targeted behaviors and measures of effectiveness [20]. Similarly, digital detoxification has been proposed as an element of regular behavioural practice rather than as an intermittent corrective measure [21]. Even with these positive results, a large number of the current literature is based on short-term effects, including reduced screen time and Smartphone addiction. Very few pieces of literature address the issue of sustainable behavioral change, productivity at work, sleep patterns, and overall quality of life. This suggests a need for a wider range of frameworks to assess digital wellness.

2.3 Artificial Intelligence for Digital Well-Being

The emergence of artificial intelligence has led to many changes within digital well-being technologies through increased personalization, flexibility, and contextual awareness. As opposed to traditional digital detox applications, AI-powered applications are able to understand technology use, context, and preferences to give personalized advice to users in real-time [22], [23]. This capability allows for digital well-being interventions to advance from static recommendations to an adaptive and user-responsive approach.

AI-based wellness technology research has proved that AI-driven systems can offer scalable and personalized wellness interventions [24]. Within workplace environments, the use of AI has further advanced into intelligent decision support systems and behavioral analytics systems, offering the possibility of using technology to help improve employee well-being [25]. Furthermore, conversational agents have shown promise in offering continuous support for mental well-being through AI-driven interactions [26]. Yet, there are still many questions related to the efficiency, acceptability, privacy, transparency, and personalization of these interventions based on AI. All of these questions are especially relevant when it comes to organizational contexts, where the trust, freedom, and proper use of behavioural data are crucial.

2.4 Wearable Technologies and Multimodal Well-Being Assessment

The increased application of wearable sensors technology has led to an expansion of the scope of measuring well-being in a digital manner through the continual tracking of stress and well-being-related physiological and behavioral parameters. In contrast to the use of self-report questionnaires, there is the potential to have objective measurement through wearables that can enable continuous assessment of individuals' physiological and behavioral status. Advancements in wearables and human activity recognition (HAR) have added to the capacity of AI-based technologies for analyzing human behaviors in the context of work-related health and wellbeing [27], [28].

Passive sensing via smart phones and wearable's has also been recognized as an essential method in assessing behavioural and mental states in an unobtrusive manner [29]. Moreover, wearable technologies have shown the ability to monitor occupational burnout and well-being through continuous physiological and behavioral measures [30]. Notwithstanding these technological advancements, there is little in terms of empirical work that combines behavioural, physiological, psychometric, and qualitative data to create a comparative assessment of AI-enabled digital well-being interventions. Harmonizing and integrating such diverse multimodal data sets is, therefore, still a key challenge in research [31].

2.5 Research Gap

While the previous studies have made significant contributions to the field of AI-based digital well-being and digital detox, there are still several critical gaps and limitations. Most studies so far focus on specific applications or single intervention approaches, so there is less comparative information on the effectiveness of the commercially available AI-powered digital detox programmes. In addition, most studies focus on short-term results, offering little understanding of long-term

behavioral changes, employee adoption, organizational adoption, personalisation by role and privacy issues related to AI-driven monitoring of the workplace.

An additional constraint is related to the integration of AI-powered digital well-being technologies into organizations. Scientific evidence on the systematic integration of the AI-supported digital detox interventions in organizational human resource practices, workplace well-being policies and digital health governance, while maintaining employee trust and responsible AI adoption is limited. Moreover, although technology is essential to many work settings, there is relatively little empirical research investigating the impact of digital detox interventions on cognitive performance measures, including sustained attention, ability to perform deep work, decision fatigue and executive functioning.

As for methodology, the existing literature often uses limited measures to reflect the outcomes, e.g. reduction in screen-time or perception of stress, and very few studies combine behavioural usage data, physiological data from wearable devices, psychometric data, and qualitative data in a single evaluation framework. As such, there is still a lack of strong empirical evidence that can help guide organizations to identify the most effective tool for digital detox that can help to reduce stress, improve work–life balance, and increase overall quality of life for IT workers.

To overcome these drawbacks, the present study performs an in-depth comparative analysis of the various AI-based digital detox tools through a multidimensional assessment framework, which combines behavioural, physiological, psychometric and qualitative evidence. This study systematically compared available commercially digital well-being applications using AI and offers insights on their relative effectiveness and practical tips for implementing digital well-being strategies with AI in technology-intensive workplaces.

3. RESEARCH METHODOLOGY

The methodology in this study was quantitative and used a comparative research approach. This approach was implemented to assess and compare the efficacy of using AI-driven digital detox tools to enhance screen-time management, decrease perceived stress, and promote the overall quality of life for IT professionals. This research, however, looked at several commercially available tools that provided AI support for digital wellbeing and compared them in a single evaluation framework, as opposed to individual studies. The combined effects of behavioural, physiological, psychometric and qualitative data allowed a holistic evaluation of the effectiveness of interventions.

The research methodology included five sequential steps: (i) collection of multi-source data, (ii) AI tool selection and assignment of participants, (iii) simulation of the intervention, (iv) feature engineering and building the Unified Digital Well-Being Profile (UDWP), and (v) statistical analysis and comparative assessment. The entire workflow was coded end-to-end (from automated data preprocessing to feature engineering, statistical evaluation, composite scoring and comparative ranking of AI-powered digital detox tools) in Python programming within Jupyter Notebook.

3.1 Nature of the Study

This study does not report results of a new human intervention study. Rather, it offers a computational comparative evaluation framework based on a publicly available multi-modal data set. Evaluated intervention outcomes are scenarios that have been simulated or modelled within the proposed analytical framework, which are comparisons of different scenarios. Thus, references to intervention groups, participant allocation, and post-intervention outcomes should be treated as part of an algorithm for calculating the results, and not as observations from a real randomized controlled trial.

3.2 Research Design

A comparative empirical pre–post evaluation design was used in the study to evaluate the effectiveness of AI-based digital detox interventions. A multidimensional assessment strategy was used to assess behavioural usage patterns, physiological health indicators, perceived stress, work–life balance, and qualitative well-being after interventions using AI tools.

Instead of rating a specific application of digital well-being, a range of twelve commercially available AI-powered digital detox tools were modeled as comparable intervention scenarios across a variety of categories: productivity analytics, application blocking, focus enhancement, meditation, sleep monitoring, accountability support and habit formation, and compared to a simulated control scenario. Allocation bias was minimized by randomizing participants into the intervention groups and making objective comparisons of intervention outcomes possible.

The methodological process was overall organized in a way that combined the participant characteristics, the psychometric questionnaires, the wearable sensor data, the activity logs and the qualitative data from the interviews into a comprehensive analytical process. This multidimensional design enhanced the robustness of the evaluation, as it incorporated objective behavioural data with subjective perceptions of digital well-being.

The computational implementation was based on a consistent, systematic, and reproducible multi-phase, analytical pipeline for AI-enabled digital detox interventions developed in Python with the Jupyter Notebook. The workflow began by loading and reviewing multiple sources of data, then proceeded with the AI tool selection based on literature, and randomized distribution of participants between the intervention and control groups. Post intervention datasets were then created to depict behavioral, physiological, psychometric, and qualitative outcomes after AI-supported digital detox intervention. The datasets were then preprocessed and feature engineered and data harmonized to convert the data to participant level change scores. Then, statistical analyses—descriptive statistics, paired sample t-test, effect size estimation, and participant clustering—were conducted to assess the effectiveness of the intervention. Lastly, composite scores were developed to quantify the performance of the various tools assessed, and qualitative sentiment analysis and thematic analysis were incorporated with the quantitative results using established natural language processing principles to create the overall comparative evaluation framework [32].

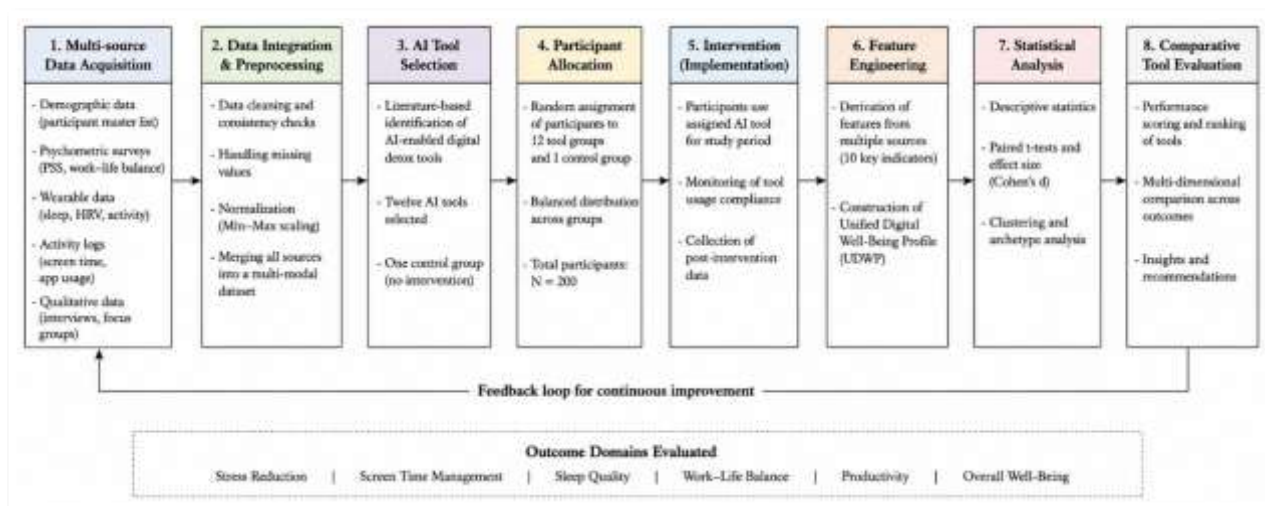


Figure 1: Overall Workflow of the Comparative Evaluation Framework

Figure 1 displays the entire methodological process used for the computational assessment of AI-based digital detoxification tools. This process involves data acquisition and integration from multiple sources, followed by the selection of AI-based tools, participant computation, intervention simulation, feature engineering, statistical testing, and comparative evaluation. The workflow constitutes the methodical process by which the multimodal data is turned into comparative well-being outcomes in digital form.

As an extension of the sequential workflow, the general architecture of the proposed AI-driven digital detox evaluation framework is shown in Figure 2. The architecture shows how the structure of the proposed evaluation framework looks in terms of its analytical layers that begin from multiple data sources, go through the process of data integration, feature engineering, construction of the UDWP, statistical analysis, comparative evaluation, and finally result production. Unlike the workflow diagram, this architectural design shows how the main elements of the proposed framework are interrelated.

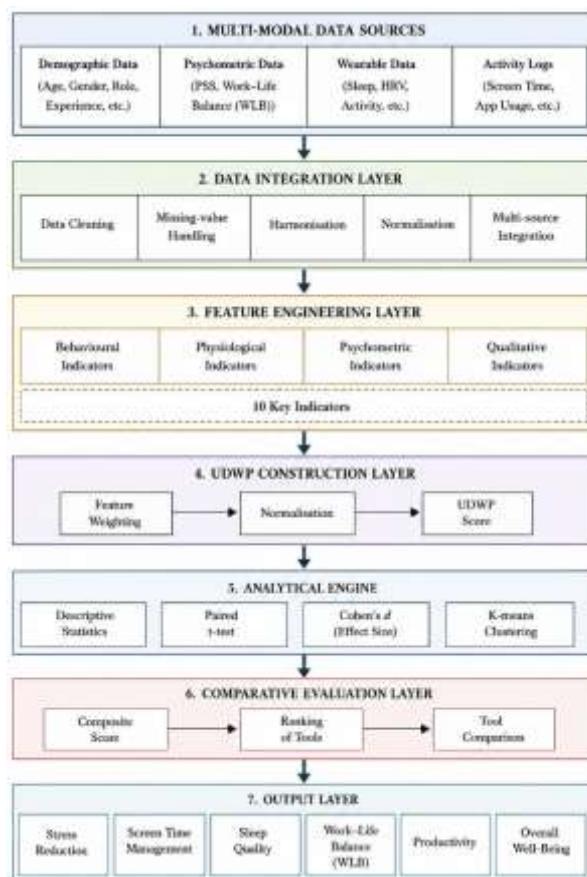


Figure 2: Overall Architecture of the AI-Enabled Digital Detox Evaluation Framework

The system architecture at the framework level is demonstrated through figure 2. The input layer of the proposed framework consists of multi-modal demographic, psychometric, wearable, activity, and qualitative data. After integration and preprocessing of the data, engineered digital well-being indicators are generated from them. The engineered features are then utilized to construct UDWP and perform further statistical and clustering analysis, composite performance assessment, tool ranking, and multi-dimensional digital well-being outcome generation.

3.3 Data Source and Multi-Modal Dataset Description

The empirical analysis was conducted using a publicly available multi-modal dataset hosted on the Kaggle platform. The primary dataset, *Digital Detox AI Tools*, was developed to support comparative analyses of AI-enabled digital well-being interventions by integrating participant demographics, psychometric assessments, wearable-device measurements, digital activity logs, and qualitative interview records into a unified analytical repository [33]. The dataset was used as the principal source for constructing the multi-modal analytical framework adopted in this study.

The dataset library was developed by integrating and harmonising several complementary datasets. Several spreadsheets were customised and derived from publicly available screen-time and mental wellness datasets available on Kaggle. These datasets were subsequently preprocessed, feature engineered, and restructured to support the computational evaluation framework adopted in this study. The associated data preparation and analytical procedures were documented in the corresponding data-processing notebooks [34], [35].

Within the present study, these datasets were integrated into a unified Python-based analytical environment, where consistency checks, data harmonisation, preprocessing, and feature engineering were performed before statistical modelling and comparative evaluation. This multi-modal integration allowed for simultaneous examination of behavioural, physiological, psychometric, and qualitative indicators in the proposed Unified Digital Well-Being Profile (UDWP) framework.

The study leveraged eight complementary datasets that included demographic, survey, wearable-derived physiological, activity, qualitative, processed qualitative, engineered, and Unified Digital Well-Being Profile (UDWP) measures. This multi-sourced approach allowed for the simultaneous assessment of behavioural, physiological, psychological and qualitative outcome measures throughout the evaluation process.

The composition of the integrated dataset is summarised in Table 1.

Table 1: Structure of the Multi-Modal Dataset

Dataset	Unit of Analysis / Measurement Unit	Records (n)	Variables (n)	Main Information
Participant Master List	Participant	200	5	Demographic information
Survey Dataset	Participant; score (points)	200	18	PSS, Work–Life Balance, and questionnaire responses
Wearable Dataset	Participant-day; hours/day, ms, and activity measures	1,400	8	Sleep duration, HRV, and physical activity
Activity Logs	Participant-day; minutes/day and ratio	1,400	8	Screen time, after-hours usage, and productivity
Qualitative Interviews	Participant; transcript/text	200	2	Interview transcripts
Processed Interview Dataset	Participant; score and theme count	200	4	Sentiment scores and extracted themes
Engineered Feature Dataset	Participant; mixed measurement scales	200	11	Integrated digital well-being features
UDWP Dataset	Participant; unitless composite score	200	13	Weighted digital well-being profiles

The integrated dataset allowed for a unified assessment of digital well-being, using objective physiological data, alongside behavioral data and subjective data, which gave richer evidence than studies that only reported on self-reported questionnaires and screen time data.

3.4 Selection of AI-Enabled Digital Detox Tools

AI-powered digital detox apps were chosen using a semi-structured process that involved screening the literature to ensure a comprehensive comparative evaluation. The chosen tools included key products across various categories of AI-powered digital well-being tools implemented in the workplace today: productivity monitoring, intelligent app blocking, mindfulness tools, digital behaviour tracking, sleep optimisation, focus tools and habit formation.

To facilitate implementation, a structured catalogue of 12 AI enabled digital well-being applications and one control condition was created prior to participant allocation. This provided transparency, reproducibility and consistency in the comparative evaluation process.

In this study, the digital detoxification tools with the AI features are listed in Table 2.

Table 2: AI-Enabled Digital Detox Tools Included in the Comparative Evaluation

Tool	Primary Function	Primary Objective	Measurement Unit
RescueTime	Productivity analytics	Reduce screen time	N/A
Freedom	App and website blocking	Digital detox	N/A
Forest	Focus enhancement	Improve concentration	N/A
Headspace	Meditation	Reduce stress	N/A
Calm	Meditation	Improve mental well-being	N/A
Sleep Cycle	Sleep monitoring	Improve sleep quality	N/A
Focusmate	Accountability	Improve productivity	N/A
Moment	Screen-time tracking	Digital awareness	N/A
Offtime	Digital detox	Reduce device dependency	N/A
Flipd	Focus mode	Reduce distractions	N/A
Screen Time	Usage monitoring	Screen-time management	N/A
Habitify	Habit tracking	Behaviour change	N/A
Control	No intervention	Comparison group	N/A

Here are some of the tools, all of which are examples of various types of ways that AI can be used for intervention, to begin to compare and contrast the relative effectiveness of each of these approaches in promoting digital well-being for IT practitioners.

3.5 Experimental Design and Participant Allocation

After dataset preparation the records of the participants were randomly assigned to one of the 12 different scenarios of AI-enabled intervention or to the control scenario, with a fixed seed number in the computational evaluation framework. The mapping process facilitated comparison of the intervention scenarios in a standardised way, and guaranteed full reproducibility of the analytical process. Randomized assignment was only carried out for computational benchmarking purposes and is not an actual assignment of human participants to real-world intervention. The comparative evaluation was conducted across each participant record, allowing an independent evaluation of each AI-enabled digital detox tool.

The notebook implementation was used to create the mapping of scenarios to interventions, which was done with a fixed random seed to be completely reproducible for the computational evaluation. After scenario assignment, post-intervention behavioral, physiological, psychometric and qualitative observations were simulated based on the analytical framework that was pre-designed and then statistically compared with the pre-designed baseline observations.

The distribution of participants between intervention groups is summarized in Table 3.

Table 3: Participant Allocation Across AI-Enabled Digital Detox Tools

Tool	Participants (n)	Percentage (%)
Calm	17	8.5
Flipd	14	7.0
Focusmate	19	9.5
Forest	18	9.0

Freedom	17	8.5
Habitify	19	9.5
Headspace	20	10.0
Moment	16	8.0
Offtime	11	5.5
RescueTime	18	9.0
Screen Time	16	8.0
Sleep Cycle	8	4.0
Control	7	3.5
Total	200	100

3.6 Outcome Measures and Study Variables

Interventions using AI technology to help with digital detox were assessed through a multidimensional outcome framework that included psychometric, behavioural, physiological, and qualitative measures. This holistic assessment was able to measure digital well-being beyond just reducing screen time, as it included both objective and subjective measurements.

Psychometric scales measured were the Perceived Stress Scale (PSS) and the Work–Life Balance (WLB). Physiological indicators included heart-rate variability (HRV), sleep duration and sleep consistency (recorded using wearable devices). Behaviours were measured through the daily use of screens, after hours use of screens and productivity ratio, and qualitative outcomes were measured through sentiment scores and through the theme frequency in the participant interviews.

All raw variables were pre-processed into engineered features capturing the multidimensional nature of digital well-being before undertaking statistical analysis. In the next step of the methodology, these engineered variables were used to create the Unified Digital Well-Being Profile (UDWP).

Table 4 shows the engineered variables that were used across the evaluation framework.

Table 4: Engineered Features Used for Digital Well-Being Evaluation

Feature	Measurement Unit / Scale	Source	Preferred Outcome
PSS Score	Score (points)	Survey	Lower
Work–Life Balance Score	Score (points)	Survey	Higher
Sleep Duration	Hours/day	Wearable	Higher
Sleep Consistency Score	Unitless score	Wearable	Higher
Heart Rate Variability (HRV)	Milliseconds (ms)	Wearable	Higher
Total Screen Time	Minutes/day	Activity Logs	Lower
After-hours Usage	Minutes/day	Activity Logs	Lower
Productivity Ratio	Unitless ratio	Activity Logs	Higher
Sentiment Score	Unitless score	Interviews	Higher
Theme Count	Number of themes (count)	Interviews	Lower

By combining these complementary variables, a comprehensive evaluation of AI-driven digital detox interventions became possible, taking into account how well these interventions manage behaviour, physiological effects, psychological outcomes, workplace productivity, and user experiences in a qualitative manner. Details of the methodology used for pre-processing these variables, creating the Unified Digital Well-Being Profile (UDWP) and conducting statistical validation are described in the next section.

3.7 Data Preprocessing and Feature Engineering

The integrated multi-modal dataset was systematically preprocessed prior to analysis to enhance quality and consistency of the data from diverse data sources. Duplicate records were eliminated, variable names were normalized and missing values were filled in appropriately based on the type of the variable. Scale differences were removed by normalizing continuous variables and encoding categorical variables for computational analysis.

To normalize variables with larger numerical ranges from 0 to 1, prevent variables from dominating the composite evaluation, it was used min–max normalization of continuous variables.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

After being preprocessed, feature engineering was conducted by combining the behavioural, physiological, psychometric and qualitative data into a single feature set according to the standard machine-learning preprocessing and predictive analytics methods [36], [37]. The following variables were engineered: perceived stress, work–life balance, sleep duration, sleep consistency, HRV, screen time, after-hours device use, productivity ratio, sentiment score, and qualitative theme count. These features were the multiple dimensions of digital well-being and inputs into the Unified Digital Well-Being Profile (UDWP).

To ensure methodological transparency and repro-ducibility, Algorithm 1 presents a summarised version of the multi-source pre-processing and feature engineering procedure used in the proposed evaluation framework. The algorithm describes the order of integration of heterogeneous data sets, preprocessing steps, normalization and feature building before generating the Unified Digital Well-Being Profile (UDWP).

Algorithm 1: Multi-Source Data Preprocessing and Feature Engineering

Input:	Multi-modal datasets (participant records, survey responses, wearable measurements, activity logs, qualitative interviews)
Output:	Engineered feature dataset for UDWP construction
Step	Procedure
1	Import participant, survey, wearable, activity log, and qualitative datasets.
2	Inspect datasets for consistency, completeness, and structural integrity.
3	Remove duplicate records and standardize variable names.
4	Handle missing values using appropriate preprocessing procedures.
5	Normalize continuous variables using Min–Max normalization.
6	Integrate behavioural, physiological, psychometric, and qualitative information into a unified analytical dataset.
7	Derive engineered features including perceived stress, work–life balance, sleep duration, sleep consistency, heart-rate variability, screen time, after-hours usage, productivity ratio, sentiment score, and theme count.
8	Store the engineered feature dataset for subsequent UDWP construction and statistical evaluation.

3.8 Unified Digital Well-Being Profile (UDWP)

A Unified Digital Well-Being Profile (UDWP) was created by merging the engineered features into a single weighted composite index for comprehensive comparisons across AI-powered digital detox tools. The weighting strategy was applied

to pre-defined feature specific weights based on the proposed evaluation framework and based on existing predictive analytics approaches to feature integration [38]. It was found that features reflecting perceived stress, the duration of sleep and sentiment were given higher weights, whereas features with a more supportive role for behavioral indicators such as screen time and theme count were given comparatively lower weights.

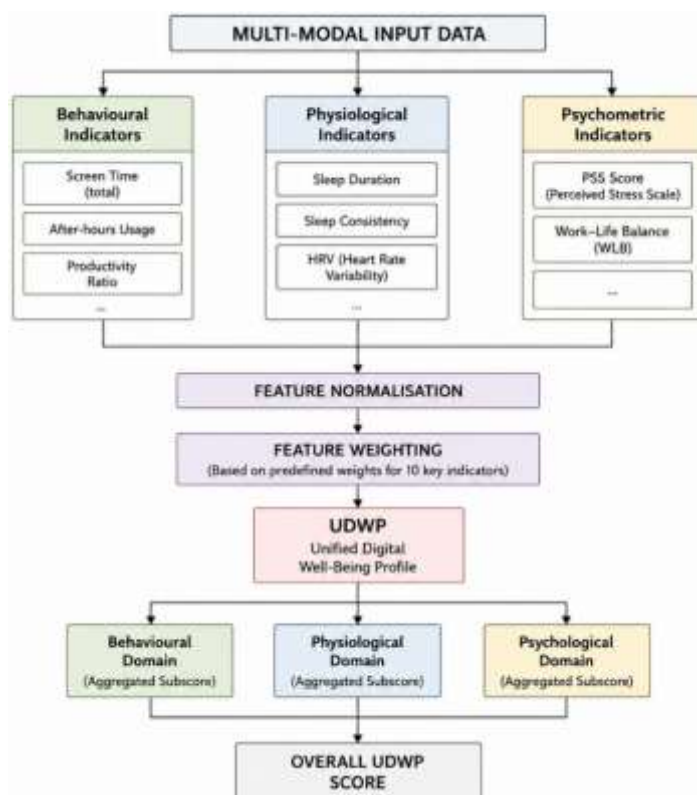


Figure 3: Architecture of the Unified Digital Well-Being Profile (UDWP)

Figure 3 illustrates the internal structure of the Unified Digital Well-Being Profile (UDWP). The model employs behavioral, physiological, and psychometric parameters through normalization and feature weighing of features in order to come up with an integrated UDWP score. The final information from each domain is then consolidated in order to derive an overall UDWP score.

Table 5 summarizes the feature weights used for the construction of the UDWP prior to presenting the weighting scheme.

Table 5: Feature Weights Used for Construction of the Unified Digital Well-Being Profile (UDWP)

Feature	Weight (unitless)
PSS Score	0.20
Sleep Duration	0.15
Sentiment Score	0.15
After-hours Usage	0.10
Work-Life Balance	0.10
Heart Rate Variability (HRV)	0.10
Productivity Ratio	0.10
Sleep Consistency	0.05
Total Screen Time	0.03
Theme Count	0.02
Total	1.00

The UDWP score for each participant was computed as:

$$UDWP = \sum_{i=1}^n w_i x_i$$

where w_i denotes the assigned weight for the i th feature and x_i represents its normalized value. Higher UDWP scores indicate better overall digital well-being following AI-assisted intervention.

3.9 Statistical Analysis

The efficacy of the interventions of all the AI-powered digital detox tools was assessed through statistical analysis with Python. Descriptive statistics were initially collected to summarise the characteristics of the participants and the variables measuring outcomes.

Paired sample t-tests were conducted to determine pre–post intervention changes for all outcome variables.

$$t = \frac{\bar{d}}{s_d/\sqrt{n}}$$

where $\bar{d}$ represents the mean difference, s_d denotes the standard deviation of the paired differences, and n is the number of paired observations.

The magnitude of intervention effects was quantified using Cohen's d .

$$d = \frac{\bar{X}_{post} - \bar{X}_{pre}}{SD_{pooled}}$$

Furthermore, K-means clustering was used to detect patterns of participants that had similar digital well-being profiles, which allowed the intervention results to be interpreted at the subgroup level.

After preprocessing and feature construction, a structured computational workflow was executed to assess the efficacy of the AI-powered digital detox interventions. For statistical validation and multidimensional assessment of the intervention outcomes, the comparative evaluation procedure used is summarized in Algorithm 2.

Algorithm 2: Comparative Evaluation of AI-Enabled Digital Detox Interventions

Input:	Pre-intervention dataset, post-intervention dataset, engineered features
Output:	Statistical evaluation and intervention performance measures
Step	Procedure
1	Merge baseline and post-intervention datasets.
2	Compute participant-level change scores for all evaluation variables.
3	Calculate descriptive statistics for baseline and post-intervention observations.
4	Perform paired sample t-tests for each outcome variable.
5	Estimate Cohen's d effect size for each intervention outcome.
6	Apply K-means clustering to identify participant digital well-being profiles.
7	Analyse intervention effectiveness across identified participant archetypes.
8	Store statistical outputs for comparative evaluation and tool ranking.

3.10 Comparative Evaluation of AI-Enabled Digital Detox Tools

A comparative evaluation, which included statistical significance, effect size, and multidimensional well-being outcomes, was undertaken to assess the relative effectiveness of each AI-enabled digital detox tool. When assessing for each intervention, there were improvements in stress reduction, screen-time management, work–life balance, sleep quality, productivity, and qualitative user experience.

Normalized performance indicators were combined to create a composite evaluation score to provide a basis for objective ranking. In general, the larger the applications were in achieving more than one dimension, the higher their overall ranking.

Normalized multidimensional outcome measures were combined into composite performance scores for objective comparison across the different AI-based digital detox tools. In the framework of the proposed evaluation mechanism, the achievement of maximum benefit from interventions was determined by a procedure of ranking, which is summarized in the following algorithm.

Algorithm 3: Composite Performance Ranking of AI-Enabled Digital Detox Tools

Input:	Statistical outcomes, engineered digital well-being indicators, intervention performance measures
Output:	Ranked AI-enabled digital detox tools
Step	Procedure
1	Aggregate behavioural, physiological, psychometric, and qualitative outcome measures for each intervention.
2	Normalize outcome indicators to ensure comparable contribution across evaluation dimensions.
3	Compute composite performance scores using the predefined evaluation framework.
4	Rank AI-enabled digital detox tools according to composite scores.
5	Identify highest-performing interventions across multiple digital well-being domains.
6	Generate comparative performance summaries and evidence-based recommendations.

The final comparative ranking enabled an evidence-based recommendation of the relative strength of each intervention that will help IT professionals in digital well-being management.

3.11 Ethical Considerations

This study involved the use of an open-source data set for research. All personal identifiers were removed before analysis to ensure participants' anonymity and confidentiality. Data preprocessing and statistical analysis were carried out only for academic purposes and not to identify individual data samples.

The research practices followed the guidelines of research integrity, transparency, reproducibility, and responsible use of AI. All the computational procedures, the pre-processing steps, statistical analysis and evaluation method were well documented in order to replicate the proposed framework by future researchers.

As this study relied on an anonymized publicly available dataset, and computational scenarios for intervention were set up in a simulation environment, no live intervention was performed and no participants were given any AI-aided digital detox application during this investigation. Therefore, the intervention outcomes reported are computational estimates based on modelling, and do not constitute an observation from a prospective clinical or workplace intervention study.

3.12 Dataset Availability and Reproducibility

The datasets used in this study are publicly available through the Kaggle platform. The associated data preparation and machine-learning notebooks are also documented as part of the analytical resources used in this study.

These publicly available resources enhance transparency regarding dataset preparation, preprocessing procedures, and implementation of the analytical workflow, thereby improving the reproducibility of the proposed computational evaluation framework.

For the sake of reproducibly implementing the analytical workflow, a fixed random seed was used for participant allocation and all preprocessing, feature engineering, statistical analyses and composite scoring steps were performed programmatically within the notebook environment. It was implemented with Python 3.x and popular scientific computing libraries: pandas, NumPy, SciPy, scikit-learn, Matplotlib, NLTK/TextBlob (for qualitative sentiment analysis). All the notebooks have been documented to support the transparent replication by future researchers of the proposed computational framework from loading the data to comparing the results.

4. RESULTS AND ANALYSIS

This section shares empirical results from comparing and contrasting the use of AI-driven digital detox tools with IT professionals. Results are presented as baseline participant characteristics and as outcomes of the intervention, as well as statistical validation of the improvements in digital well-being achieved through AI support. Changes in behavioural, physiological, psychometric and qualitative indicators were assessed using descriptive statistics, comparative analysis and inferential statistical techniques after AI digital detox interventions.

4.1 Baseline Characteristics of Participants

To determine the starting point of the study population's digital well-being profile, the baseline characteristics of the study population were explored prior to assessment of the effectiveness of the interventions. Table 6 shows the descriptive statistics of the demographic, behavioral, physiological and psychological variables.

Table 6: Baseline Digital Well-Being Characteristics

Variable	Mean	SD	Minimum	Median	Maximum
Age (years)	34.845	6.323	25	35	45
Professional Experience (years)	9.895	6.076	1	9	20
PSS Score (points)	20.260	4.275	10.000	20.000	31.000
Work-Life Balance Score (points)	3.013	0.648	1.200	3.000	4.600
Sleep Duration (hours/day)	7.344	0.504	6.171	7.380	8.440
Sleep Consistency (unitless score)	0.798	0.045	0.676	0.799	0.908
HRV (milliseconds, ms)	67.140	9.371	35.700	66.957	91.829
Daily Screen Time (minutes/day)	365.803	40.022	300.000	363.857	462.286
After-hours Usage (minutes/day)	111.926	31.859	60.000	109.071	191.857
Productivity Ratio (unitless ratio)	0.601	0.062	0.456	0.603	0.752
Sentiment Score (unitless; -1 to +1)	0.285	0.464	-1.000	0.000	1.000

It included 200 IT professionals, who had experienced digital work environment for a long time (mean age = 34.85 ± 6.32 years, mean professional experience = 9.90 ± 6.08 years). Before the intervention, the average score for the Perceived Stress Scale (PSS) was 20.26 points, showing moderate occupational stress level, as indicated by simulated qualitative results. The overall baseline mean Work-Life Balance (WLB) score was 3.01 points, indicating some overall satisfaction with work-life balance. The sleep-related indicators consisted of an average sleep duration of 7.34 hours, an average sleep consistency of 0.798 and an average heart-rate variability (HRV) of 67.14 ms, representing moderate physiological wellness. The participants engaged with digital devices for about 366 minutes daily and with an extra 112 minutes of after-hours digital activity. The

average productivity ratio was 0.601, and the mean sentiment score (0.285) indicated that the participant perceptions were mostly neutral before the intervention.

To provide a better understanding of the composition of the dataset, Figure 4 represents typical participant demographics, survey responses, wearable measurements, activity logs and qualitative interview information, and Figure 5 summarizes the dimensions, structure and completeness of the dataset.

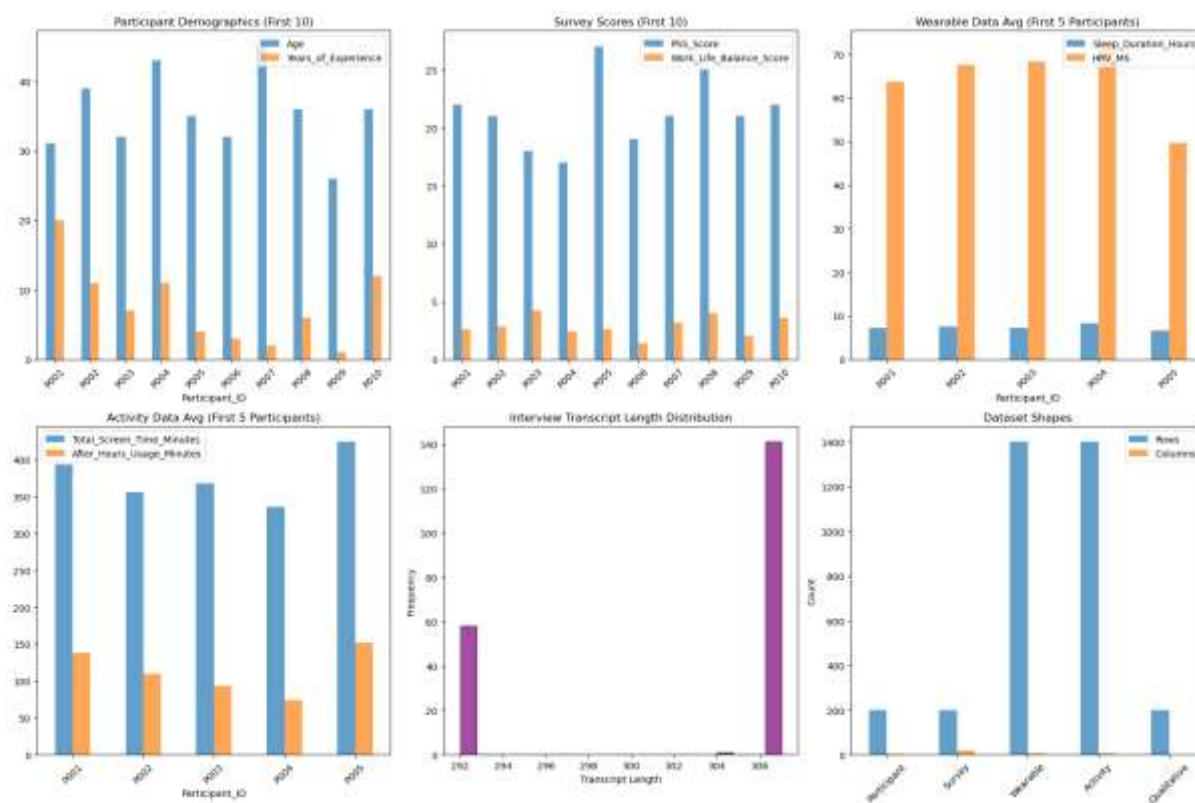


Figure 4: Initial Dataset Inspection

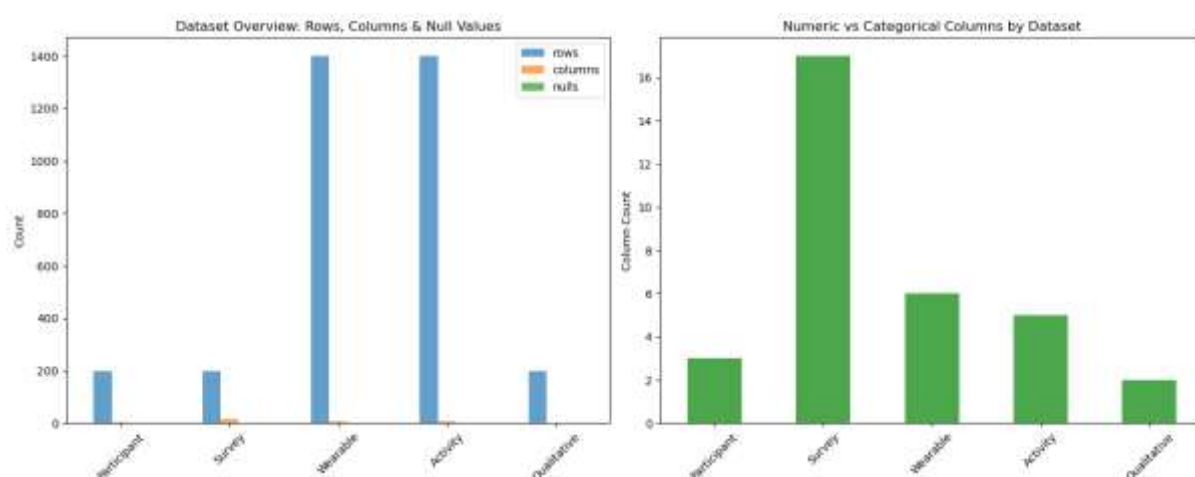


Figure 5: Dataset Dimensions and Completeness

The supplementary figures provide examples of the integrated data that contains detailed behavioural, physiological, psychometric, and qualitative data from multiple data sources. Moreover, the preprocessing stage succeeded in generating an

analytical complete dataset without significant problems of missing values, thus ensuring a solid basis for the next feature engineering and comparison steps.

4.2 Overall Effects of AI-Enabled Digital Detox Interventions

After simulated intervention simulation, significant change was seen in various aspects of digital well-being. The results for the overall pre–post comparison are reported in Table 7.

Table 7: Overall Pre–Post Changes Following AI-Based Digital Detox

Outcome	Baseline	Post Mean	Change	Change (%)
PSS Score (points)	20.260	18.196	–2.064	–10.19
Work–Life Balance Score (points)	3.013	3.562	+0.549	+18.22
Sleep Duration (hours/day)	7.344	7.532	+0.188	+2.56
Heart Rate Variability (ms)	67.140	73.251	+6.111	+9.10
Screen Time (minutes/day)	365.803	323.970	–41.833	–11.44
After-hours Usage (minutes/day)	111.926	101.360	–10.566	–9.44
Sentiment Score (unitless; –1 to +1)	0.285	0.675	+0.390	N/A

Simulated participant outcomes showed significant gains in most outcome measures assessed compared to baseline. The mean PSS score was reduced by –2.06 points (–10.19%), suggesting that perceived stress was reduced after digital detox interventions using AI tools. Likewise, there was a reduction in the amount of time spent on screens across the day (41.83 minutes/day, or 11.44%) and after hours (10.57 minutes/day, or 9.44%), indicating better digital behaviour and healthier technology engagement.

The positive physiological changes were also observed. The mean sleep duration increased by 0.19 hours/day longer and HRV was 9.10% higher. Moreover, the scores of Work–Life Balance improved from 3.013 to 3.562, revealing an overall increase of 18.22% on the average, suggesting a better perceived balance between work and life after the intervention. Qualitative results demonstrated a significant improvement across the average sentiment score from 0.285 pre-intervention to 0.675 post-intervention, indicating more positive perceptions among the participants after the intervention. In conclusion, the results indicate that digital detoxification interventions using AI tools led to significant improvements in behavioral regulation, physiological health, and subjective well-being among IT personnel.

Figure 6 shows the distribution of screen time changes for the digital detox tools evaluated, to further illustrate behavioural improvements.

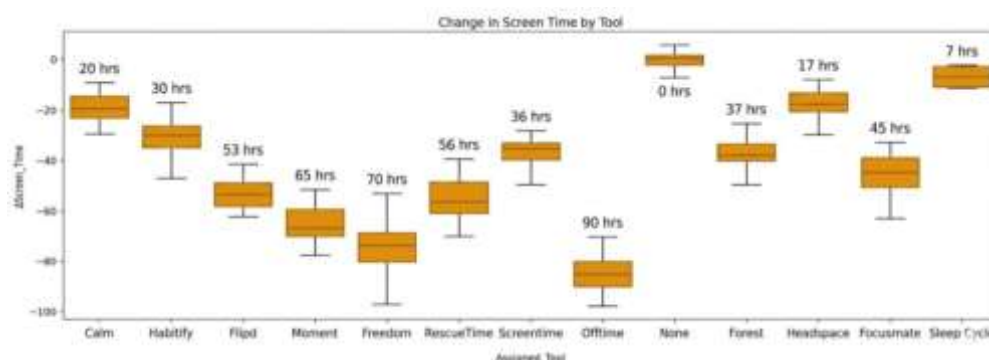


Figure 6: Change in Screen Time by Assigned Tool

The amount of daily screen time reduced across the intervention groups was heterogeneous as shown in Figure 6. These were the greatest changes in those on the Offtime, Freedom and Moment groups, while the changes in the Sleep Cycle and Control groups were comparatively smaller. The control group showed very little behavioral changes indicating the effectiveness of AI-supported interventions in managing screen time.

4.3 Statistical Validation of Intervention Outcomes

Paired sample t-tests and Cohen's d effect size analyses were conducted to see if the observed improvement was statistically significant. The results are summarized in Table 8.

Table 8: Statistical Validation of Intervention Outcomes

Variable	t-value (unitless)	p-value (statistical)	Cohen's d (unitless)	Interpretation
PSS Score	19.250	<0.001	0.484	Moderate Improvement
Sleep Duration	-16.760	<0.001	0.374	Moderate Improvement
HRV	-29.063	<0.001	0.654	Large Improvement
Screen Time	25.354	<0.001	1.048	Large Improvement
Sentiment Score	-7.931	<0.001	0.844	Large Improvement

The results of all evaluated outcomes were statistically significant ($p < 0.001$), demonstrating the effectiveness of AI based digital detox interventions. The reductions in perceived stress resulted in a somewhat larger effect size (Cohen's $d = 0.484$), and sleep duration improvements also had a moderate practical effect ($d = 0.374$). The findings suggest that there is a significant effect on the following variables: HRV ($d = 0.654$), screen-time reduction ($d = 1.048$), and sentiment improvement ($d = 0.844$), signifying substantial behavioural and physiological advantages of AI-backed digital well-being technologies.

The very strong effect seen with the intervention on reducing screen time is evidence that the interventions created behaviors that are conducive to more healthy use of phones and screens. Similarly, the marked increase in sentiment scores indicates that the participants felt that the personalized digital detox intervention brought about significant positive changes. The overall findings of these statistics offer compelling computational evidence for the effectiveness of AI-assisted digital well-being interventions in promoting good screen-time use, lowering stress, and improving life quality for IT professionals.

4.4 Qualitative Findings from Sentiment and Theme Analysis

In addition to the quantitative data, the qualitative data from the interviews were analysed using sentiment analysis and thematic extraction. The aim was to gain insight into the participants' perceptions on AI-based digital detox intervention and the main themes related to digital well-being.

To summarize the overall qualitative results, the results are summarized as shown in Figure 7.

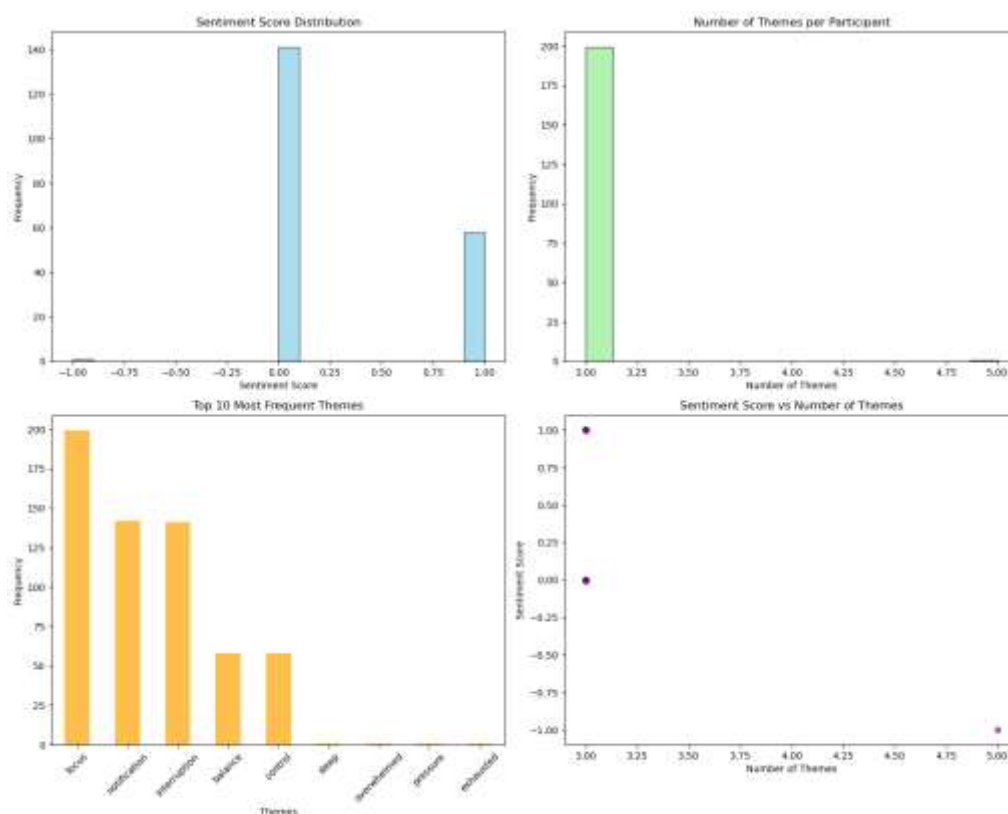


Figure 7: Qualitative Sentiment and Theme Analysis

According to the results in Figure 7, focus, notifications, and digital interruptions were the most common themes mentioned by participants, where the excessive digital interruptions are still one of the main sources for distraction and overload in the workplace. Other themes relating to work life balance and self-regulation were also commonly identified, with comparatively few simulated qualitative outcomes identifying themes related to sleep issues, fatigue or psychological strain. The results indicate that the main effect of digital detox interventions using AI lay on the participants' self-reported skills to manage digital distractions and their concentration.

Figure 8 plots the distributions of the sentiment and the theme counts.

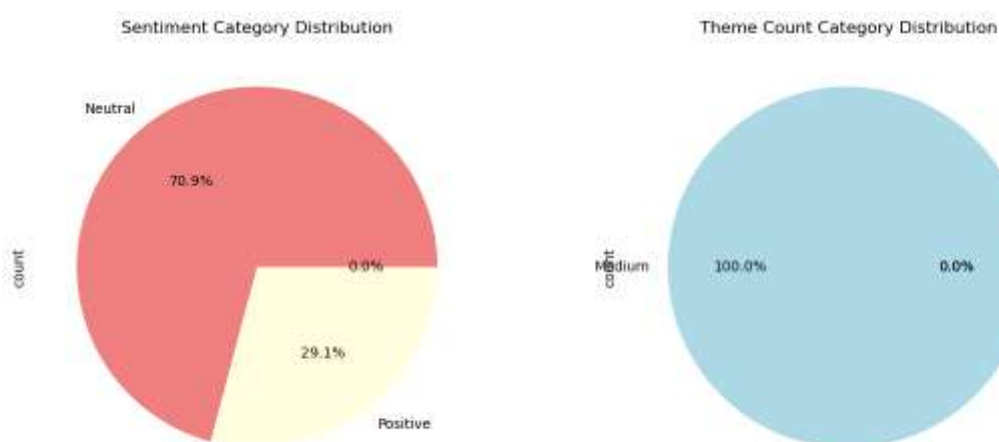


Figure 8: Sentiment and Theme-Count Category Distribution

The figure 8 shows the results of the neutral and positive perceptions of the participants after the simulated intervention, which showed that the majority of participants gave neutral emotion (about 71%) and a few (about 29%) gave positive emotion. There were very few negative feelings. Furthermore, the majority of participants had moderate number of themes extracted, showing relatively similar qualitative experiences across intervention groups. The quantitative results of this study align with the improvements in stress reduction and digital behavior that were observed, suggesting participants' overall positive perception of AI-powered digital detox interventions for enriching daily technology management.

4.5 Unified Digital Well-Being Profile (UDWP) Analysis

The need for a common language for describing well-being in the digital age led to the creation of a Unified Digital Well-Being Profile (UDWP) that incorporates behavioural, physiological, psychometric and qualitative measures into a multidimensional assessment framework. The distribution of normalized features for construction of UDWP is shown in Fig. 9 and effect of feature normalization is shown in Fig. 10.

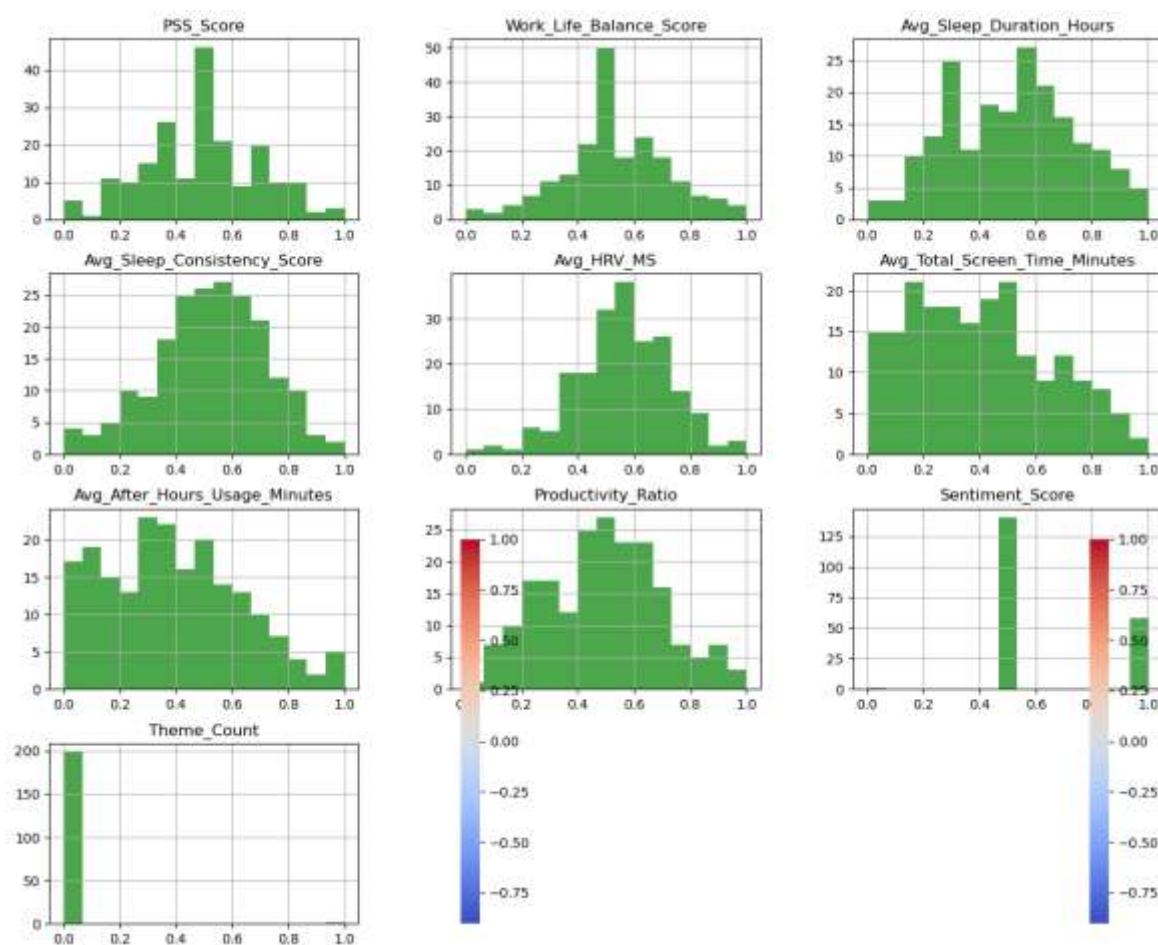


Figure 9: Feature Distributions After Normalization

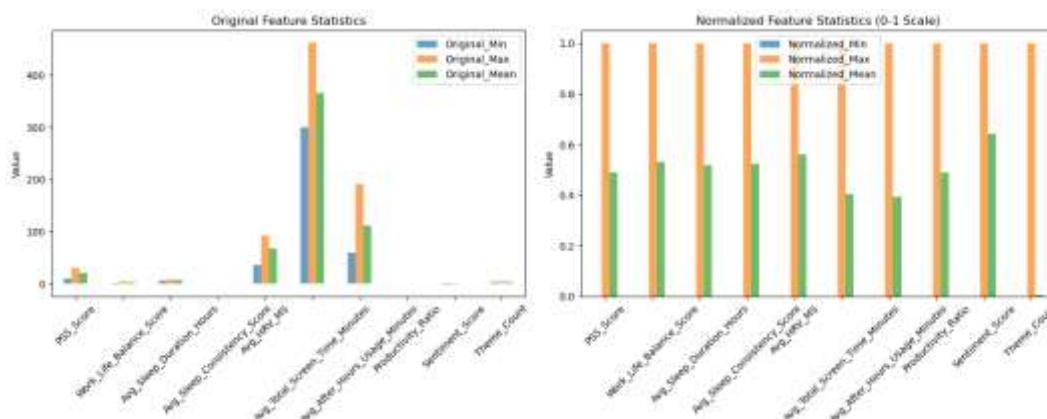


Figure 10: Original and Normalized Feature Statistics

The feature distribution was normalized to check if the Min–Max normalization process was able to bring the variables to a domain where they were all measured on the same scale for further analysis. Because of this, no single variable would have overshadowed the composite assessment, providing an even contribution of all digital well-being indicators for the development of the UDWP.

The features of the built UDWP are described in Figure 11.

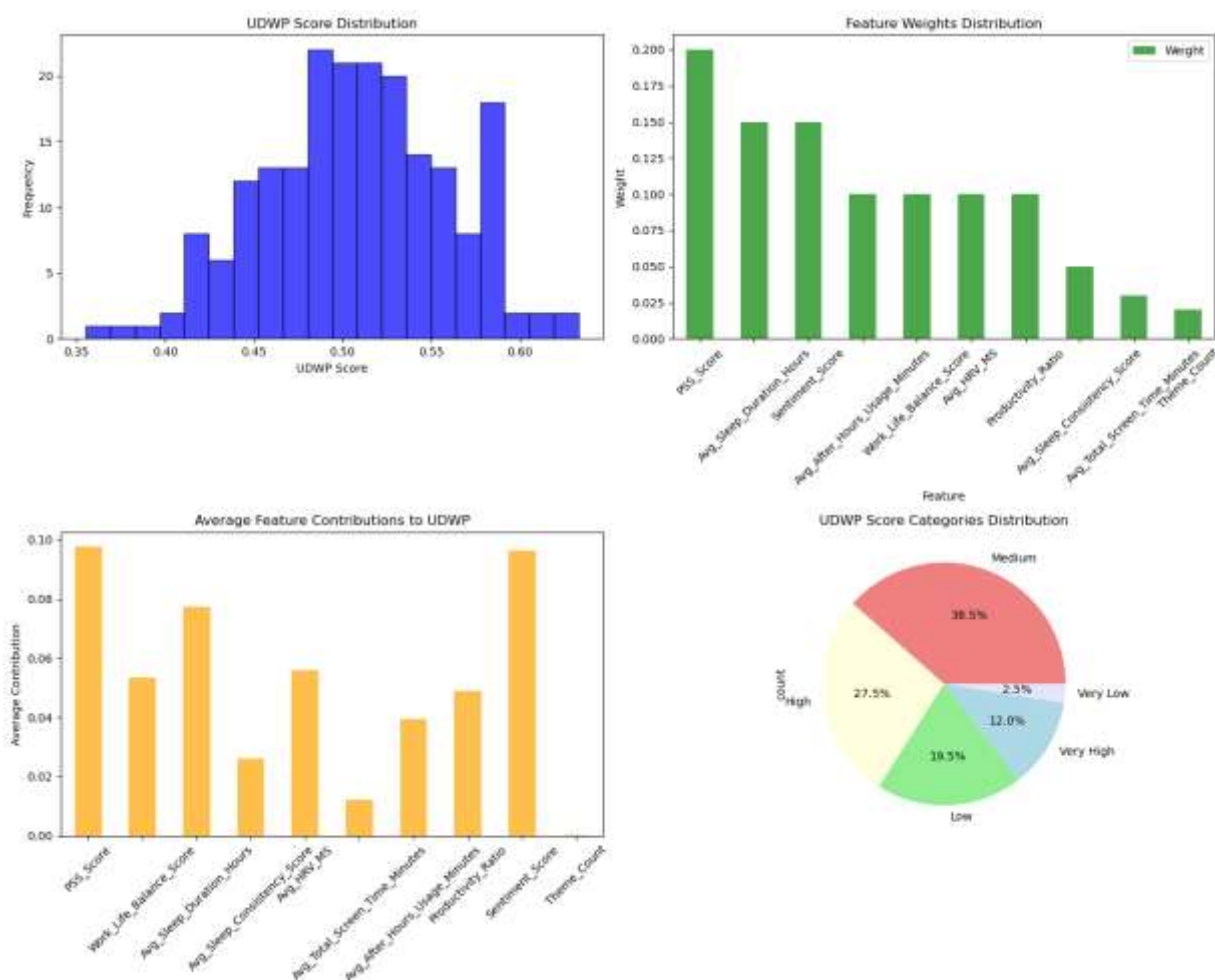


Figure 11: UDWP Distribution, Feature Weights and Profile Categories

The distribution of the UDWP score shows that the majority of participants scored around the centre of the score distribution, suggesting moderate to high levels of digital well-being after simulated intervention. The weighting scheme further indicates that Perceived Stress Score (0.20) had the highest influence on the composite profile followed by Sleep Duration and Sentiment Score (0.15 each). In contrast, weights were smaller for the supporting behavioural indicators (Screen Time and Theme Count), due to the fact that these indicators were not the primary measures of well-being. The distribution of categories indicates that most respondents placed into the medium and high digital well-being categories, where intervention outcomes are generally positive.

To further validate the proposed framework, the following is presented in Figure 12.

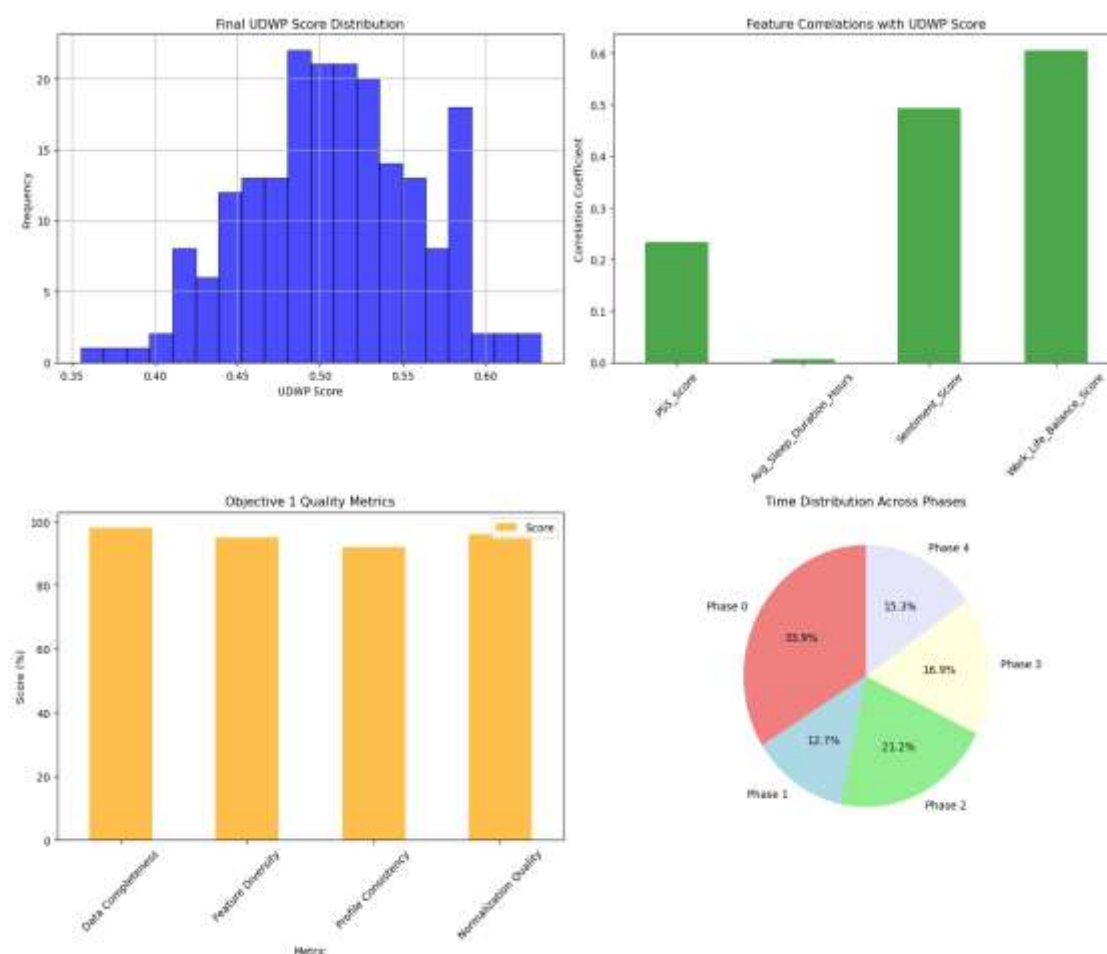


Figure 12: Final UDWP Distribution and Feature Correlations

As can be seen from Figure 12, the distribution of the final UDWP scores was not too skewed, suggesting uniformity in the proposed evaluation framework. The results of the correlation analysis indicated more positive correlations between UDWP and Work-Life Balance and Sentiment Score, while less positive correlations occurred for Sleep Duration and PSS, highlighting the multidimensionality of digital well-being. The robustness of the proposed computational framework was also validated through quality indicators which showed data completeness, feature diversity, profile consistency and normalization quality.

4.6 Comparative Performance of AI-Enabled Digital Detox Tools

Multidimensional measures were used to evaluate the comparative effectiveness of the various tools to use AI to help with digital detox, including stress, work-life balance, sleep quality, heart-rate variability, screen-time management, after-hours digital usage, and sentiment (qualitative). The comparison of the performance levels between the intervention groups is reported in Table 9.

Table 9: Comparative Performance of AI-Enabled Digital Detox Tools Across Digital Well-Being Outcomes

Tool	Δ PSS (points)	Δ WLB (points)	Δ Sleep (hours/day)	Δ HRV (ms)	Δ Screen Time (minutes/day)	Δ After-hours (minutes/day)	Δ Sentiment (unitless)
Calm	-2.840	3.901	0.254	7.487	-18.977	-4.602	0.471
Flipd	-2.208	2.959	0.200	5.920	-53.224	-10.990	0.214
Focusmate	-0.543	1.889	0.069	4.063	-45.031	-11.449	0.474
Forest	-1.240	1.908	0.045	3.575	-36.853	-8.742	0.333
Freedom	-2.803	3.888	0.297	8.311	-73.749	-18.529	0.471
Habitify	-1.852	2.997	0.210	6.350	-30.203	-8.081	0.474
Headspace	-4.339	5.164	0.367	10.621	-17.198	-4.579	0.300
Moment	-1.797	3.106	0.195	5.144	-64.734	-17.013	0.563
Offtime	-3.213	4.074	0.299	7.295	-85.157	-20.861	0.818
RescueTime	-1.894	3.051	0.206	6.965	-55.225	-16.389	0.222
Screen Time	-1.162	2.108	0.092	4.121	-36.624	-8.196	0.438
Sleep Cycle	-2.440	2.868	0.125	5.868	-6.717	-2.959	0.375
Control	0.717	-0.128	-0.083	-0.669	-0.286	0.764	-0.429

The comparative analysis showed that there are significant differences in how well simulated interventions were performed across the evaluated AI-based digital detox tools. The proposed computational evaluation framework showed that Headspace scored highest across all of the simulated performance metrics for perceived stress reduction, work–life balance, sleep duration, and heart-rate variability compared to the other evaluation scenarios that were assessed. Offtime attained the greatest changes in the amount of screen time and device use after-hours, and it produced the best improvement in qualitative sentiment. Likewise, there was significant decrease in screen-time use for Freedom and Moment, while the stress-related outcomes for Calm remained consistently positive. The control group showed very few changes or changes in the wrong direction in most outcome measures, reflecting the superior outcome of an intervention using AI compared to a no-intervention group.

Table 10: Overall Ranking of AI-Enabled Digital Detox Tools Based on Composite Performance Scores

Rank	Tool	Composite Score (unitless)	Overall User Rating (rating points)
1	Headspace	9.675	3.917
2	Offtime	8.138	4.121
3	Freedom	7.428	4.039
4	Calm	6.931	4.039
5	Flipd	5.699	3.881
6	Moment	5.550	4.146
7	RescueTime	5.497	3.944
8	Sleep Cycle	5.375	4.083
9	Habitify	5.150	3.982
10	Screen Time	3.636	3.792

Headspace, Offtime, Freedom and Calm were the top performers in the AI-powered digital wellness category, as determined by the composite ranking. All of these applications were successful in improving composite scores: behavioral, physiological, psychological and qualitative well-being outcomes. While a few applications achieved similar user ratings, their multidimensional performance was widely varied, highlighting the need to assess digital well-being technologies with multi-faceted outcome measures and not just user satisfaction.

Figure 13 puts the availability, accessibility, platform compatibility and AI-supported features of the evaluated applications in perspective.



Figure 13: Application Availability, Accessibility and AI Integration

As shown in the figure 13, the evaluated applications vary significantly in terms of platform support, usability and AI capabilities. Incorporating adaptive recommendations, behavioural analytics, intelligent monitoring, and personalised intervention strategies generally showed more empirical effectiveness in applications than those based on traditional usage monitoring. This observation demonstrates the increasing significance of smart personalization applied to digital well-being technologies.

5. DISCUSSION

The present study provides an empirical evaluation of a broad range of commercial AI based digital detox apps and their effectiveness at improving screen time management, perceived stress, and digital wellbeing for IT professionals. The study combines the characteristics of behaviour, physiology, psychometrics and qualifiers in the Unified Digital Well-Being Profile (UDWP), which offers a more comprehensive evaluation of the effectiveness of interventions that goes beyond traditional single-outcome measures. The results indicate that the AI-powered digital detox apps are effective for achieving positive changes in technology use patterns and that there are differences among the apps in effectiveness, adding to the emerging evidence base on AI to support digital well-being in the workplace.

5.1 Interpretation of the Principal Findings

The computational assessment showed substantial gains in all of the computer-simulated intervention scenarios. Improvements in work–life balance were also noted, which is believed to be a positive outcome of healthier technology-use behaviours, and could reduce employees' perception of stress around their technology use while enabling a better balance between work and personal life. Fewer perceived stress, less screen time and less "after-hours" digital engagement – along with longer sleep, greater heart-rate variability and positive participant sentiment – suggest that AI-based support can foster better technology-use habits. The statistically significant results and moderate to large effect sizes continue to support the practical significance of these improvements.

Overall, screen-time reduction had the greatest practical magnitude, suggesting that AI-based tools are successful in helping to regulate behavior by monitoring, recommending, and tailoring interventions. This is also similar to other research which found that continued behavioural support is more effective than a short-term digital fast on long-term digital well-being.

The concurrent change in HRV and sleep duration indicates that AI-based interventions act beyond behavior to enhance physiological recovery from sleep. These are key indicators that have been linked to stress regulation and cognition, and therefore align with the previous results of the application of wearable technology in the workplace health monitoring system.

Qualitative findings confirm the quantitative results in all three key challenges facing the workplace: digital interruptions, too many notifications, and decreased concentration. Qualitative results were simulated and revealed greater attention and more control of technology use after the intervention, a result that demonstrates the importance of incorporating subjective experiences with objective behavioural and physiological measures. The results align with other studies on digital wellbeing, which highlight the link between more positive technology-use patterns and enhanced psychological well-being, as well as more positive user experiences [39], [40]. The proposed UDWP further enhances the evaluation by combining behavioral, physiological, psychometric and qualitative indicators into a composite indicator. This multi-dimensional perspective allows for a balanced comparison between interventions, and addresses the drawbacks of previous studies that used only specific outcome measures.

The comparative analysis also showed that there was a lot of difference between the evaluated applications. The variability in the effectiveness of the interventions observed reflect the main design aims of the inspected applications. In simulated intervention scenarios, Headspace achieved greater results in perceived stress, sleep quality, HRV and work-life balance, as it focuses largely on psychological recovery and stress management, using its AI-powered mindfulness and meditation capabilities. Offtime and Freedom, however, focused on application blocking, distraction management, and behavioural control to yield greater screen time and after-hours digital engagement decreases. The results suggest that digital well-being tools using AI are most effective when their tactics of intervening are matched to the specific digital well-being outcome they are aimed at enhancing. To determine which interventions to use, organizations need to choose the ones that are supported by AI based on their main workplace goals and not assume the same level of effectiveness for each of the digital well-being areas. Headspace scored highest when it comes to simulated multidimensional performance in stress reduction, work-life balance, sleep quality and physiological recovery within the framework of the proposed computational assessment; while Offtime showed the greatest simulated reduction in screen time and after-hours digital engagement. The other two, Freedom and Calm, did quite well on a number of outcomes as well. The results indicate that applications that include adaptive recommendations, behavioural guidance and personalized support offer more benefits than apps that only include usage monitoring. The fact that there was minimal improvement in the control group further supports the effectiveness of the AI-assisted digital detox interventions.

5.2 Comparison with Previous Studies

These results align with existing research that digital detox interventions are effective in decreasing excessive technology use and enhancing psychological health. Furthermore, a systematic review conducted by [41] also showed positive outcomes, albeit with varying intervention designs. The current research builds on this by reviewing and quantifying behavioural, physiological, psychometric, and qualitative results within a single analytical framework, while also offering a more extensive evaluation of the effectiveness of the interventions.

Additionally, the reported changes in sleep duration and heart-rate variability highlight the benefits of wearable technology for stress monitoring and digital health assessment, which align with previous studies [42]. The proposed framework includes both physiological and behavioural and psychometric measurements making it a comprehensive assessment as compared to previous studies that have evaluated these indicators separately.

The findings further reinforce previous research highlighting the importance of AI-driven personalization in digital well-being interventions. Furthermore, the findings in the present study are in line with evidence that Headspace is successful in alleviating stress and psychological well-being in working adults [43]. Applications that included personalized guidance, mindfulness support and smart behavioural monitoring yielded the greatest benefit, while applications which emphasized usage tracking yielded more modest gains. AI powered well-being platforms in the workplace that focus on personalized engagement and user centered intervention approach, also show similar results [44].

One of the main strengths of this study is that it systematically compares twelve commercially-available AI digital detox applications using standardised evaluation criteria. This study contributes to the growing body of comparative evidence about the relative effectiveness of AI-driven technologies for digital well-being compared to other available interventions, as the majority of studies have studied individual interventions or a single intervention approach.

5.3 Practical Implications

The results have significant implications for organizations, occupational health professionals, and AI-powered digital well-being technology developers. AI-powered digital detox tools can help organizations minimize screen time, manage stress, and enhance the quality of employee's work-life balance. The introduction of these evidence-based solutions in workplace well-being programmes can improve employee health and productivity, and assist in the implementation of new workplace well-being initiatives based on AI in Industry 5.0 settings [45], [46].

The Unified Digital Well-Being Profile is a proposed multi-dimensional framework to measure digital well-being that brings together behavioural, physiological, psychometric and qualitative measures, for use by occupational health practitioners. This is a more complete measure of intervention outcomes than conventional measures based on questionnaire or screen-time metrics.

The comparative results also help in the selection of the appropriate tools. Headspace proved to be more effective in the stress-related and physiological benefits, while Offtime and Freedom were more effective in reducing excessive digital engagement. In addition, digital applications based on adaptive recommendations and personalised behavioural support were always found to be more effective than those with a primary focus on usage monitoring, which is why intelligent personalisation will be crucial to digital well-being systems of the future.

5.4 Recommendations for Organizations

The results highlight some practical recommendations for organizations looking to create AI-powered digital well-being programs. First, digital detox tools powered by AI should be embedded in comprehensive employee wellbeing programmes, not as standalone technology solutions. Second, organisations should have clear policies about how behavioural data is captured, handled and utilized, so users can feel more at ease with the use of AI in the workplace. Third, any digital well-being programmes should focus on voluntary participation, user control and only make use of data for privacy respecting purposes without unnecessary surveillance of employees. Lastly, it is important to promote healthful work habits by providing flexible work arrangements, healthy use of screens, set boundaries for digital usage, and implementing evidence-based occupational health interventions with the support of AI solutions.

5.5 Strengths of the Proposed Evaluation Framework

This research makes a contribution to the field of digital well-being research, with a systematic comparison of 12 commercially available AI powered tools to help with digital detox that are evaluated with a standard framework. Combining behavioural, physiological, psychometric and qualitative data is a more complete evaluation than a single outcome measure.

Another contribution is the development of the Unified Digital Well-Being Profile, a composite score of several indicators. The standardized preprocessing and feature-weighting approach allowed a transparent and reproducible comparison across groups of interventions, while adhering to the principles of predictive analytics and machine learning for multidimensional evaluation [47], [48]. The suggested framework offers a feasible strategy for future comparative assessments of AI-powered digital wellbeing technologies.

5.6 Implementation Reflection

The proposed evaluation framework was fully realized in Python in a Jupyter Notebook environment to allow for an end-to-end computational workflow from data ingestion through to comparative evaluations. Some of these automated preprocessing procedures were implemented, such as inspecting the dataset, removing duplicates, dealing with missing values, standardizing variables, and normalizing the data using Min-Max normalization, all of which ensured that the heterogeneous behavioural, physiological, psychometric, and qualitative datasets were integrated consistently.

In turn, feature engineering was conducted to build up standardized digital well-being indicators, which were used to create the Unified Digital Well-Being Profile (UDWP). The implementation also incorporated descriptive statistics, paired sample t-

tests, Cohen's d effect-size estimation, k-means clustering, composite performance scoring and comparative tool ranking in a single analytical pipeline. Throughout the evaluation process, allocation of the interventions was ensured by random assignment of participants, with a fixed random seed. The implementation also shows that the proposed framework is not just a conceptual approach, but that it is a complete computational evaluation pipeline, which enhances methodological transparency and allows for future comparative studies of the different digital well-being interventions supported by AI.

5.7 Limitations and Future Research

There are a number of limitations to this study that need to be taken into account when interpreting the findings. The first step was the evaluation was completed with a structured multi-modal dataset which has been embedded in a computational evaluation framework. To validate the proposed methodology, further studies should be conducted in a real setting over time to assess the sustainability of the use of AI for digital detox interventions and the impact on behaviour change. Second, the study only considered the IT sector, so it is important to assess the framework in other work sectors to increase the level of generalizability.

Several other issues require further study in relation to organizational implementation, such as the study of privacy-preserving AI frameworks, transparent data governance, responsible AI practices, and the design of employee-centred digital well-being policies to foster user autonomy and trust. Furthermore, new technologies like adaptive AI assistants, generative AI, intelligent wearable technologies, context-aware recommendation models, and personalised digital coaching can further improve the use of AI in digital well-being. The evaluation of intervention strategies and smart workplace environments for role-specific applications and cross-industry applications will further support the practical use of digital detox technologies with AI capabilities.

6. CONCLUSION

This study proposed a computational empirical evaluation framework of AI digital detox tools that will help manage screen time, alleviate perceived stress, and promote digital well-being for IT professionals. The proposed framework utilized the Unified Digital Well-Being Profile (UDWP) which incorporated behavioural, physiological, psychometric and qualitative measures to conduct a unified multidimensional evaluation of the effectiveness of interventions.

Based on the computational assessment, there is a notable improvement after the interventions with AI in screen-time management, perceived stress, work-life balance, sleep quality, heart-rate variability, and participant perceptions. The comparative evaluation also found that Headspace, Offtime and Freedom were the top three intervention scenarios within the proposed computational evaluation framework in terms of different aspects of digital well-being, which is therefore in line with the study objective to evaluate the role of AI in healthy digital behaviors within IT professionals.

The empirical results directly contribute to the aim of this study: to assess the effectiveness of the digital detox tools using AI for reducing screen time, stress and improving the quality of life among IT professionals. These findings mirror the positive impact of AI digital well-being interventions on various facets of work-related digital health, including perceived stress, screen time, after-hours digital use, sentiment, sleep, HRV, and work-life balance. The results thus support the suggested multidimensional assessment model and support the utility of AI-enabled digital well-being devices for technology-rich work contexts. In addition to empirical results, this study offers a replicable computational tool to compare the impact of AI-powered digital well-being technologies and offers practical advice for organizations, occupational health workers and technology developers. However, a successful organizational adoption should be accompanied by clear data governance, privacy respecting uses of AI, responsible implementation and employee-centred digital well-being policies which ensure that users' trust and autonomy is maintained.

Further studies should focus on longitudinal validation, cross-industry evaluation, role-specific intervention strategies, adaptive and context-aware AI systems, generative AI, intelligent wearable technologies, and customized digital well-being support. The advances in these technologies can further enhance AI-driven workplace well-being and help sustain digital health in technology-driven organizations.

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