

# Analysing the Impact of AI-Based Digital Detox Interventions on the Health and Lifestyle of IT Professionals

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## ABSTRACT

The high rate of workplace process digitalization has been accompanied by the high exposure of information technology (IT) professionals to screens, which has contributed to the rise of stress, cognitive exhaustion, and unbalanced lifestyles. Traditional digital detox programs usually depend on self-control and do not provide adaptive and personalized support, which limits the effectiveness in the long term.

This study is a proposed simulation-based analytical model to address the feasibility of using AI-assisted digital detox intervention as a means of enhancing digital behavior, perceived stress, mental health, and lifestyle balance. Kaggle provided a secondary dataset of responses to 300 IT professionals, which was analyzed with machine learning models, such as Logistic Regression, Support Vector Machine (SVM), Random Forest, and K-Means clustering. To model the behavioral logic of digital detox strategies in a dozen of representative AI-based well-being apps, a hybrid intervention model that combines predictive analytics with rule-based behavioral logic was created.

The results show that in the context of the simulation, AI-based interventions are linked to the reduction of screen time by nearly 30%, perceived stress level by 40% - 45% and the increase of the mental well-being and lifestyle indicators by more than 40%. SVM was the most predictive model (F1-score = 0.82), and then there was the Random Forest (F1-score = 0.70) among the tested models.

Such findings indicate that AI-based digital detox models can offer a scalable and context-sensitive technology-intensive way to promote digital health. The results are however, model estimates and they have to be confirmed by real world implementation studies.

**Keywords:** Artificial Intelligence; Digital Detox; IT Professionals; Stress Prediction; Mental Well-Being; Screen Time Analytics; Lifestyle Improvement.

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## 1. Introduction

The massive embrace of digital technologies has had a great impact on the workplaces today especially in the information technology (IT) industry where work processes largely rely on constant contact with digital systems. Although this type of technology has helped people be more productive, more connected, and more efficient in their work, there is growing evidence that the result of long-term exposure to digital technology is higher levels of stress, cognitive burnout and mental health decay, and work-life imbalances. These issues point to the increasing necessity of effective and dynamic measures to facilitate sustainable IT-related well-being among information technology specialists.

### 1.1 Digital Overexposure in the IT Sector

IT professionals work in well-connected spaces with constant screen time and professional-personal life boundaries. Development of software, virtual working, and constant monitoring of the real-time

system are routine activities that cannot be disconnected with the digital devices. As a result, digital overexposure has become a significant work-related issue, which leads to the psychological exhaustion, burnout, and decreased life quality. These impacts are in line with the literature on technostress that has been able to cite technology overload and constant connectivity as the two significant sources of occupational strain [1].

### 1.2 Health Consequences of Prolonged Digital Use

IT professional work is intertwined with the rise of stress and burnout which is frequently provoked by the constant connection, performance pressure and inability to have a cognitive rest [2]. These are in line with previous studies conducted on technostress where it has been established that it negatively affects user satisfaction and performance in technology heavy settings [3]. Spending an excessive amount of time in online spaces is also a cause of cognitive overload, which leads to a lack

of focus, mental exhaustion and decreased productivity. Other previous researches have also demonstrated that repetitive digital distractions and notifications have a profoundly negative effect on attention and productivity [4]. Moreover, the high screen time has adverse effects on lifestyle trends, causing sedentary behavior, sleep disorders, and work-life disproportion. All these psychological and lifestyle conditions promote the necessity to follow effective and technology-based interventions that may potentially help in the long-term digital well-being. Overuse of social networking sites has also been associated with sleep disturbance and identity-related stress among the users [5, 6].

### **1.3 Limitations of Conventional Digital Detox Approaches**

Conventional methods of digital detox, including voluntary limits on screen time and planned offline time, can be short-term only. These are not adaptive in terms of feedback and do not provide personalized instructions but depend on self-control of an individual. Consequently, their performance is still not full, especially in occupations that are digitally intensive. Thus, a greater need is in more responsive, adaptive, and context-relevant intervention strategies. There is empirical evidence that the temporary benefits of disconnection to digital communication like decreased email use can positively impact focus and productivity, but are not long term sustainable [7].

### **1.4 Emergence of AI-Based Digital Well-Being Interventions**

Artificial intelligence (AI) has presented new possibilities of providing adaptive, personal, and data-driven solutions to digital health. The expanding digital mental health focuses on how technology-enabled interventions can enhance quality and access to care [8, 9]. The AI based systems can track the user behavior continuously, identify the stress patterns in real time and offer context-related recommendations based on individual working habits and health needs. The innovations of personal sensing and machine learning allow permanently measuring behavioral and mental conditions by digital signals [10]. This can be done by using machine learning methods with behavior-based nudging systems to create intelligent intervention systems that are scalable and user oriented [11].

### **1.5 Research Motivation**

Although the area of AI-based digital well-being solutions has gained increased interest, the current literature is sparse in terms of implementation-focused empirical research in the real-world occupational setting. Most of the previous research is based on theory or experimental, controlled environments, and little is done on applied, data-driven evaluation. The proposed study will seek to fill this gap as it will consider the role of AI-

assisted digital detox programs on IT professionals in digital behavior, stress, mental health, and lifestyle balance.

### **1.6 Contributions of the Study**

The study is an addition to the expanding literature on the topic of digital well-being since it illustrates how machine learning models can be used to determine stress, mental, and lifestyle factors in a digitally intensive work setting. It introduces a digital detox system, which is an AI-based intervention system that combines predictive analytics with behavior-focused intervention strategies. The research also offers some practical information on how companies could use AI-based solutions to improve employee welfare and facilitate sustainable digital behaviour.

### **1.7 Organization of the Paper**

The rest of the paper is organized in the following way. Section 2 includes a general overview of the conceptual and empirical literature available on the topic of digital well-being and AI-based interventions. Section 3 provides the research objectives that provide guidance to the study. The dataset, data collection procedure, and methodology of implementation are explained in sections 4 to 7. The sections 8 to 10 present the analytical framework, AI tools and system implementation. The results and discussion are found in sections 11 and 12, respectively. Lastly, Sections 13 to 15 address ethical issues, conclusions, limitations, and future research directions. The structure is aimed at making the conceptual foundation to empirical analysis and interpretation have logical progression.

## **2. Conceptual and Empirical Background**

The section is aimed at providing the conceptual and empirical basis of the suggested framework. Work practices have been altered tremendously by the growing number of digital technologies being applied in working environments especially in the IT industry. Inasmuch as these developments have enhanced efficiency and teamwork, they have come with issues of overexposure to screens, work-related stress, psychological exhaustion.

### **2.1 Digital Usage Patterns and Health Risks Among IT Professionals**

The long-term use of screens and constant interaction with the digital world have led to less time to recover psychologically, leading to the further development of cognitive load and mental exhaustion, according to Marciano et al. (2024) [12]. In a similar fashion, Marx et al. (2025) [13] define digital detox in the organizational setting and underline that the main cause of emotional and cognitive burnout is under the guise of constant connectivity.

Gupta et al. (2024) [14] also state that overuse of digital tools is one of the major causes of stress and emotional burnout in practitioners. In line with this opinion, Kolhe and Naik (2025) [15] show that the

overload of digital connection has a harmful impact on the eudaimonic well-being as it destroys the psychological balance. Together, these investigations create a robust connection between the long-term effects of digital exposure, technostress, and deteriorating mental wellbeing in workplaces of a high demand [16]. Such results are also justified by studies that prove that technostress does have quantifiable biological and cognitive effects on people [17].

Also, Uslu (2025) [18] states that excessive screen time is a factor that leads to sedentary lifestyles, sleep disruptions, and work-life imbalance. The evidence presented by Pan et al. (2025) [19] suggests that the quality of sleep and lifestyle balance can be improved by means of structured digital detox interventions, which point to the direct effect of digital habits on the overall quality of life. These results highlight the significance of the interventions that include both psychological and lifestyle aspects of well-being. Overuse of smartphones has also been linked to lack of productivity and daily disruptions at workplaces [20].

## 2.2 AI-Based Interventions for Digital Well-Being

The AI-based systems have proven to be very promising with regard to shaping digital behavior by means of continuous monitoring and feedback. As pointed out by Adanyin (2024) [21], AI-based feedback systems can be used to create awareness of overuse and behavioral control. Likewise, Malik and Tennakoon (2025) [22] demonstrate that the use of monitor-screen technologies that are integrated into mobile applications can favor healthier digital behaviors because they allow them to receive real-time feedback [23].

More developments in machine learning have made it possible to recognize and forecast stress based on behavioral and physiological information. The article by Ta et al. (2025) [24] proves that machine learning models are effective in detecting patterns of stress and allowing timely intervention [25]. Shin (2025) [26] points out the need to make AI systems human friendly when creating digital well-being solutions, which must not be intrusive to the user and must be ethical.

Also, Khoziashveva (2025) [27] emphasizes the value of user-oriented AI applications in decreasing the level of digital addiction by providing context-specific behavioral prompts. The more recent advances in the field of deep learning have increased the possibilities of AI in the domain of health care analytics and decision support systems [28]. Zannat and Mahmud (2023) [29] also show that the design of user experience at a mindful level can decrease the addictive tendencies and enhance the well-being [30]. All of these studies highlight the role of personalization and behavioral alignment in the improvement of the effectiveness

of AI-based interventions. Healthcare systems that are AIs are becoming more and more a combination of human and machine intelligence to enhance decision-making and patient outcomes [31].

Similar studies by Jiménez-Gonzalez et al. [32] and Putrevu and Mertzanis (2025) [33] also contribute to the generalizability of AI-based lifestyle interventions in enhancing the overall health outcomes [34], which supports the validity of AI-based interventions in fostering sustainable digital well-being.

The recent empirical data also helps to ensure the effectiveness of digital detox interventions that are organized and studied, where researchers report the quantifiable positive changes in the levels of anxiety and depression after exposure to the controlled intervention among young adults [35].

Conversational agents and mobile-based therapies are digital mental health interventions that have been shown to help in the promotion of psychological well-being [36]. Systematic reviews have also validated the usefulness of digital mental health interventions in reducing the symptoms of depression and anxiety [37], and meta-analyses indicate the effectiveness of smartphone-based interventions in psychological support [38].

## 2.3 Identified Research Gaps

Although the amount of literature has increased, some gaps are still present. To begin with, even though theoretical and conceptual literature reveals the possible advantages of AI-based digital detox interventions, the existing empirical data on the outcomes of these interventions in terms of stress reduction, mental health, and lifestyle balance are scarce [39, 40].

Second, most of the available literature is done under controlled or experimental conditions, which restricts their applicability to occupational settings. This limits the application of the results to other professional populations like IT workers where digital exposure has been integrated into routine work processes.

Third, lifestyle-related consequences like the quality of sleep, physical activity, and work-life balance are relatively less studied as compared to psychological ones. Combined behavioral, psychological, and lifestyle analyses are underrepresented in the current literature [41]. Also, the discrepancies in the definition and measurement of problematic use of digital use are still a weakness in the current literature [42].

## 2.4 Role of Existing Literature in Framing the Study

The theoretical foundation of the research is previous studies conducted on digital addiction, work-related stress, and technology-induced well-being. Tabish (2025) [43] and SA (2025) [44] define the concept of digital addiction as a new public health issue, and Erdemir and Atik (2025) [45] focus on the idea of AI-based promotion of

human-centered digital well-being [46]. The previous studies also emphasize the complicated connection between the use of digital technology and well-being outcomes, which are context-specific and depend on patterns of its use [47].

A systematic review like that by Ramadhan et al. [48] points to the scarcity of large-scale, implementation-based studies assessing AI-based digital detox programs in the workplace. These results support the necessity of empirical studies that go beyond conceptualizations to applied analytical analysis.

The choice of the key outcome variables was also informed by the existing literature, which consisted of screen time, stress levels, mental well-being, and lifestyle balance. Moreover, it informed the selection of machine learning models and formulation of behavior-based intervention logic in such a way that the analytical framework is rooted in existing research and meets the gaps that have been identified before. In order to give a systematic synthesis of the available literature, Table 1 outlines the main studies concerning digital well-being, digital detox measures, and AI-based health analytics. The table brings out the methodological strategies, main findings, and limitations of previous studies, thus providing a comparative outlook and supporting the research gaps to be filled in the current study.

**Table 1. Summary of Key Literature on Digital Well-Being and AI-Based Interventions**

Author (Year)	Study Focus	Methodology	Key Findings	Limitation
Marciano et al. (2024)	Digital detox & well-being	Empirical study	Reduced stress and improved well-being	Limited occupational focus
Marx et al. (2025)	Digital detox framework	Conceptual	Identifies burnout due to connectivity	Lacks empirical validation
Gupta et al. (2024)	Digital stress in professionals	Observational	High digital exposure linked to burnout	Healthcare-focused sample
Kolhe & Naik (2025)	Well-being & detox	Analytical	Detox improves psychological balance	Limited sample diversity
Malik et al.	Technostress in	Empirical	Strong link	No AI-based

(2025)	workplace		between workload and stress	intervention
Pan et al. (2025)	Detox & lifestyle	Experimental	Improved sleep and lifestyle balance	Focus on adolescents
Ta et al. (2025)	ML for stress detection	ML-based study	High accuracy in stress prediction	Controlled setting
Shin (2025)	Human-centered AI	Review	AI must be ethical and non-intrusive	Conceptual only
Ramadhan et al. (2024)	Detox meta-analysis	Systematic review	Detox reduces anxiety and stress	No occupational data
Torous et al. (2020)	Digital mental health	Review	Tech improves access to care	Limited behavioral modeling

### 3. Implementation-Oriented Research Objectives

The analytically defined objectives of the study include:

- 1) To assess how AI-based digital detox interventions are connected to the variation in mean daily screen time among IT professionals in a simulation-based environment.
- 2) To determine the association between AI-supported logic of intervention and changes in the perceived stress, mental well-being, and indicators of lifestyle balance.
- 3) To compare the predictive accuracy of machine learning algorithms (Logistic Regression, SVM, Random Forest, and K-Means) in stress and well-being states classification.
- 4) To investigate the feasibility factors of implementation level, such as privacy, behavior adherence, and usability, in a simulated digital well-being system run by AI.

### 4. Implementation Dataset and Data Provenance

An organized and trustworthy data is necessary to analyze the effects of AI-based digital detox programs. This study will employ a secondary data source that is publicly available so as to achieve

methodological consistency, ethical compliance and reproducibility.

#### 4.1 Public Kaggle Dataset

The data employed in the present research is the Screen Time vs Mental Wellness Survey (2025) available on Kaggle [49] which is one of the well-known open-access resources on machine learning and data science studies. Kaggle datasets are widely used in machine learning studies because of their availability, structured form and ability to be analysed in a reproducible manner. The dataset was chosen because it is directly related to the study objectives as it includes important variables which are associated with digital behavior, stress levels, mental well-being as well as lifestyle balance of working professionals. The sample will include 300 IT professionals, which will offer adequate variability in terms of descriptive analysis as well as predictive analysis.

#### 4.2 Dataset Variables

The data set incorporates the following variables of importance:

- **Screen Time:** The level of digital exposure is expressed as an average time of digital device use daily.
- **Stress Score:** Perceived stress with self-reported measure on standardized psychological measures.
- **Mental Well-Being Score:** Measure of psychological health based on reliable instruments, like the WHO-5 Well-Being Index.
- **Lifestyle Indicators:** Multidimensional measures such as sleep quality, physical activity and work-life balance.

These are the variables that are commonly considered to be core indicators in the digital well-being and occupational health research.

#### 4.3 Participant Characteristics and Representativeness

The data used in the research lacks specific demographic characteristics like age, gender, work roles, experience in years, or geographical distribution of the sample. Consequently, the sample representativeness of the sample concerning the wider population of IT professionals cannot be evaluated completely. This weakness can impact the external validity of the results because the differences in demographic and professional variables can impact digital behaviors, stress levels, and well-being outcomes. Next time, more detailed demographic profiling should be included in the studies to allow more powerful and generalized analysis.

#### 4.4 Analytical Relevance of the Dataset

The dataset allows achieving several analytical goals, such as:

- Risk patterns that are linked to over-exposure to digital exposure

- Machine learning models of stress and well-being prediction training and validation
- Comparison of pre- and post-assessment in an AI-based intervention system
- Evaluation of the digital behavior and its association with health outcomes

The multidimensionality of the data allows using machine learning models, including Support Vector Machine, random forest, logistic regression, and K-Means clustering, to analyze the data in a comprehensive manner.

#### 4.5 Tool-Wise Pre-Post Evaluation Design

In order to analyze AI-based intervention of digital detox, a pre-post layer of analysis was added. Data of participants were successfully mapped systematically within various modules of AI interventions so as to allow comparative evaluation of the results. The variables of post-intervention were calculated to signify changes in:

- Screen time
- Stress levels
- Mental well-being

This is a designed study that allows measuring the impact of interventions within a controlled analytical framework without undermining ethical standards due to the utilization of anonymized secondary data.

### 5. Data Collection Method

The research design used in this study is secondary data research, which will be conducted to analyze the effects of AI-based digital detox interventions on IT professionals and their health and lifestyle. There was no primary data collected since the study uses solely the publicly available, anonymized survey data.

#### 5.1 Secondary Data Acquisition

I sourced the data on the Kaggle open-source platform, which offers structured datasets in research and analytical work. The chosen dataset comprises the variables concerning the behavior of digital usage, stress level, mental health, and lifestyle tendencies among IT professionals. There are several benefits associated with the application of secondary data:

- Provides ethical standards by using anonymized data
- Enhances transparency and reproducibility
- Gives freedom to concentrate on analytical modelling and framework development

This method is specifically appropriate when applied to machine learning and digital health analytics studies that take on an implementation focus.

#### 5.2 Health and Well-Being Assessment Instruments

- **Perceived Stress Scale (PSS):** The scale is used to assess the perceived stress levels with respect to unpredictability, workload, and lack of control.

- **WHO-5 Well-Being Index:** Assesses psychological functioning, such as mood, vitality, and overall psychological functioning.
- **Lifestyle Indicators:** Add sleep quality, physical activity and work/life balance which gives a more comprehensive view of well-being.

The tools are well-established and common in the occupational health and digital well-being studies.

### 5.3 Relevance to Study Objectives

The method of data collection justifies the assessment of the most important outcome variables, such as screen time, stress levels, and mental well-being, and lifestyle balance. The empirical validity and reliability of the analysis is improved by the use of standardized instruments.

### 6. Sample Size Description

An adequate sample size is essential in reliability, generalizability, and analytical prowess of machine-learning-based research on health assessment. The data of 300 IT professionals employed in the present research will be a great sample in every stage of the descriptive analysis, the predictive modelling, and the pre- and post-assessment. The right sample size is crucial in terms of reliability and analytical robustness of machine learning-based studies.

#### 6.1 Dataset Size

The article is based on a sample of 300 IT professionals, which gathers a wide range of behavioral and psychological variables associated with online use and well-being.

#### 6.2 Effective Analytical Sample

All 300 records were stored after preprocessing, such as cleanup of data, and normalization and encoding. There were no major missing values or discrepancies in the dataset, which means that it will be fully utilized in the analysis.

#### 6.3 Justification of Sample Size

The number of samples of 300, however, is enough to perform machine learning-based classification and clustering. It offers enough variability to detect patterns, predictive models and intervention outcomes. This understanding is comparable to previous research on occupational health and behavioral analytics.

Machine-learning-wise, a dataset like this is large enough to be trained and tested on classification and clustering models, such as the Logistic Regression, Support Vector Machine, Random Forest and K-Means clustering, without the need to run the risk of over fitting. The sample may be statistically employed to determine the performance measures and make valid pre- and post-comparisons of stress, well-being and lifestyle indicators. Moreover, the occupational health researchers tend to consider 200-400 people as enough to evaluate the behavioral and psychological process, which explains why the

chosen dataset is reasonable to apply this investigation which is implementation-oriented.

## 7. Implementation Methodology and Analytical Design

This section makes the conceptual bases in the literature operational by describing the methodology of implementation to be used in the paper. The presented framework is an analytical design with the implementation or implementation-focused simulation design to assess the efficiency of AI-based digital detox interventions on the health and lifestyle of IT professionals. The method combines the machine learning-based analytics and behavior-conscious intervention logic to provide the empirical rigor and practical applicability.

### 7.1 Research Design

An analytical design with structured pre- post evaluation framework was used based on a simulation design. The results were compared with baseline measures such as screen time, perceived stress, mental well-being, lifestyle balance, and the post-intervention outcomes that were produced using the AI-based analytical framework. It is worth mentioning that the pre- after results are obtained in a simulated analytical setting with the help of secondary data and thus, are modeled estimates of actual effects of real-world interventions. The design allows the assessment of the impact of interventions in the situation when it is not possible to have a randomized experimental design.

### 7.2 Methodological Framework

The overall analytical workflow is composed of several interdependent phases that help in the process of data processing, predictive modelling, generation of interventions, and outcome assessment.

#### 7.2.1 Data Ingestion and Preprocessing

The data that was received at Kaggle was systematically preprocessed to create analytical coherence. This involved cleaning and normalization of numerical variables, encoding of variables of type, and checking data integrity. These measures guaranteed the compatibility of all machine learning models and reduced noise in the dataset.

#### 7.2.2 Feature Extraction

Relevant features were chosen depending on their correspondence to digital well-being indicators:

- **Usage indicators:** daily screen time intensity
- **Health indicators:** perceived stress scores and measures of mental well-being
- **Lifestyle indicators:** balance in work and life, consistency of routine

The domain knowledge and research objectives informed the feature selection process to make sure that the behavioral and psychological aspects were represented meaningfully.

#### 7.2.3 AI-Based Health Modelling

Health outcomes were analyzed through machine learning models to predict them:

- Stress classification using Logistic Regression
- Support Vector Machine (SVM) of mental well-being classifier
- Random Forest of integrated health outcome prediction
- K-Means clustering of patterns of digital usage

These models offer supplementary predictive and descriptive technologies to the association between digital behaviour and occupational well-being.

The overall analytical pipeline under consideration in the study is shown in Figure 1 that presents the end-to-end workflow, starting with the acquisition of the datasets and ending with AI-based health prediction and intervention generation.



**Figure 1. End-to-End AI-Based Digital Detox Analytical Workflow**

As illustrated in Figure 1, the workflow is structured in a sequence where it starts with the dataset acquisition then goes through preprocessing and feature extraction. Predictive insights are subsequently produced by using machine learning models and are processed as the inputs of the digital detox intervention engine. This pipeline will guarantee a methodological conversion of raw

behavioral data to health-related insights, which can be acted upon.

**7.2.4 Digital Detox Intervention Logic**

Hybrid intervention mechanism was created through the combination of predictive models results and rule-based behavioural reasoning. Depending on the estimated stress and usage, the system produces context-oriented recommendations, such as:

- Relaxation and mindfulness stimuli
- Screen-time regulation strategies
- Concentration improvement and marathon planning
- Lifestyle improvement nudges

This methodology will make interventions individualized, adaptive and in line with individual behavioral patterns.

**7.2.5 Comparative Evaluation of Outcomes**

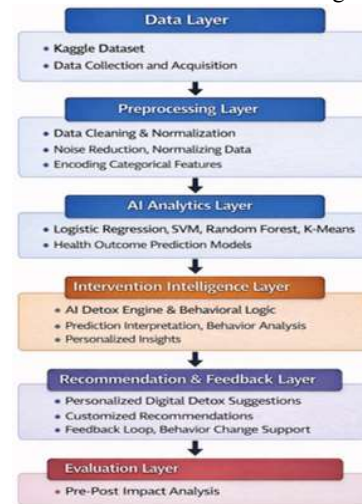
Changes in pre and post interventions indicators were compared to identify the changes:

- Screen time
- Stress levels
- Mental well-being
- Lifestyle balance

Accuracy, precision, recall, and F1-score were used to measure model performance. The trend of the outcomes was also analyzed in terms of graphical and statistical presentation to make the results interpretable.

**7.3 System Architecture of the AI-Based Digital Detox Framework**

To convert the analytical process into a scalable and modular system, the proposed structure was designed into a layered architecture that combined data processing, predictive analytics, intervention intelligence, and evaluation system. Figure 2 shows the architecture of the proposed system and shows how data moves between various functional layers to facilitate AI-based interventions in digital detox.



**Figure 2. Architecture of the AI-Based Digital Detox Framework**

The system will consist of the following layers as illustrated in Figure 2:

- **Data Layer:** Anonymized secondary information on digital behavior, stress, mental well-being, and lifestyle indicators in the stores.
- **Preprocessing Layer:** Manages data cleaning, normalization and encoding of data to be used in modeling.
- **AI Analytics Layer:** Applies prediction and pattern recognition machine learning models.
- **Intervention Intelligence Layer:** Converts analytical outputs into actionable behavioral strategies.
- **Recommendation and Feedback Layer:** Gives customized digital detox consultation and dynamic feedback.
- **Evaluation Layer:** Performs pre-post analysis to assess intervention effectiveness.

Such a layered architecture increases scalability, interpretability, and modular integration of analytical and intervention components, and this increased practical applicability of the proposed framework.

### 8. AI Tools and Intervention Framework

Here, the framework of analysis is expanded to operationalize the predictive outputs into digital well-being interventions that can be taken into action. The suggested system will take a hybrid approach in which machine learning-based predictions are used and structured behavioral logic to simulate AI-assisted strategies of digital detox are adopted.

#### 8.1 Intervention Logic and Behavioral Mapping

The intervention strategies were determined by a rule-based decision layer that translated the predictive outputs of the machine learning models into intervention strategies. This layer translates analytical information to user-based recommendations hence delivering contextual and personalized intervention.

The intervention logic will be organized into the following:

- **Stress Risk Stratification:** Predicted levels of stress are used to place the users into low, moderate, and high-risk categories. This type of classification allows the prioritization of intervention intensity.
- **Usage Pattern Interpretation:** Behavioral segments like excessive usage, moderate usage and balanced usage patterns are identified using clustering outputs, which enables target design of interventions.
- **Personalized Digital Detox Recommendations:** The system provides

recommendations like based on joint predictive understanding such as:








- Screen-time regulation strategies
- Mindfulness and relaxation prompts
- Focus-mode activation and break scheduling
- Digital boundary reinforcement mechanisms
- **Lifestyle-Oriented Nudging:** Other behavioral cues such as posture reminders, hydration and exercise reminders are also included to stimulate overall well-being.

This hybrid reasoning guarantees that the intervention strategies are flexible, customizable and in line with individual behavioral traits.

#### 8.2 Integration of AI-Based Digital Well-Being Tools

In order to replicate real-world applicability, some of the most popular AI-based digital well-being tools were cross-mapped to categories of interventions. These are tools that were not implemented directly but were abstractly used to depict functional intervention modules as part of the framework.

**Table 2. AI Tool-to-Intervention Mapping**

SL No.	AI Tool	Core Intervention Feature
1.	 Calm AI	Mindfulness and stress relief
2.	 Headspace AI	Guided meditation
3.	 Wysa AI	Conversational stress support
4.	 Mindstrong AI	Mental-health analytics
5.	 Sensa AI	Emotional intelligence nudges
6.	 Woebot	CBT-based chat support
7.	 Youper	Mood tracking
8.	 Replika (WB Mode)	Emotional companionship
9.	 happify AI	Positive psychology support
10.	 Fitbit AI Coach	Lifestyle and activity nudges
11.	 Google Digital Wellbeing	Screen-time regulation
12.	 Microsoft Viva Insights	Screen-time regulation
13.	 Google Digital Wellbeing	Screen-time regulation
14.	 Microsoft Viva Insights	Work-life balance analytics

The tools were classified according to their major functional abilities:

- **Mindfulness and Stress Support:** Calm AI, Headspace AI, Wysa AI, Woebot
- **Mental Health Analytics:** Mindstrong AI, Sensa AI, Youper
- **Emotional and Behavioral Support:** Replika, Happify AI
- **Lifestyle and Activity Coaching:** Fitbit AI Coach
- **Screen-Time and Productivity Regulation:** Google Digital Wellbeing, Microsoft Viva Insights

These tools are exemplary modules that demonstrate how the current AI systems can be used to facilitate digital detox interventions in work settings.

### 8.3 Simulation-Based Tool Evaluation Framework

An analytical layer in the form of a structured pre- and post-evaluation of the possible effects of AI-based interventions was created. It is necessary to underline that, all the intervention results reported in this study are model estimates that are produced in a simulation-based analysis system and are not the real-world measurements of experimental application of the tools. The assessment plan consists of:

- Behavioral indicators of baseline based on the data set
- Model-predicted simulated intervention exposure
- Post-intervention outcome estimation
- Comparison between important health indicators.

This will allow the effectiveness of the interventions to be assessed in a controlled manner without issue of methodological transparency.

## 9. System Implementation and Execution Framework

This section explains the technical aspects of the implementation of the proposed framework such as computational environment, model execution pipeline, and simulation-based evaluation process.

### 9.1 Computational Environment

The framework was applied with the help of an open-source computational ecosystem to make the framework transparent and reproducible.

- **Programming Language:** Python
- **Execution Environment:** Interactive notebook-based environment
- **Libraries Used:**
  - pandas (data processing)
  - numpy (numerical computation)
  - scikit-learn (machine learning models)
  - matplotlib (visualization)
  - scipy (statistical operations)

Standardized pipelines were used to run all the preprocessing, modelling and evaluation procedures to ensure consistency.

### 9.2 Data Preprocessing and Preparation

The dataset was preprocessed systematically before being executed in the model:

- Eradication of discrepancies and duplication of records
- Normalization of the numerical variables (screen time, stress, well-being)
- Categorical variables can be encoded
- Validation of dataset completeness (n = 300 retained)

These measures have guaranteed analytical consistency and compatibility with machine learning models.

### 9.3 Model Training and Evaluation Strategy

To test the predictive performance, the dataset was split into training and testing to obtain 80:20.

Standardized features were used to train the models and test them:

- Accuracy
- Precision
- Recall
- F1-score

The performance measures give an approximation of the reliability of classification in the analytical platform.

### 9.4 Digital Detox Recommendation Engine

A hybrid recommendation engine was adopted to transform predictive results into interventions to be taken.

To achieve the goal of deploying analytical results to actionable interventions, a hybrid recommendation architecture had been implemented, consisting of a layer of predictive (predicts the well-being status and stress) and behavioral logic (provides context-specific recommendations).

It was a system of certain help (mindfulness, screen exposure, and break) in the case of the high level of stress detected and a special support. The outcomes of the usage intensity and clustering were employed to produce adaptive alerts like focus-mode-activation, early-warning of prolonged use and multitasking-reduction-cue. The recommendations will be supportive, realistic, and behavioral in accordance to the occupational requirements to the design.

The system integrates:

- **Predictive Layer:** Determines the level of stress and behavioral patterns
- **Decision Layer:** Involves rule-based intervention selection
- **Recommendation Layer:** Generates context-aware suggestions

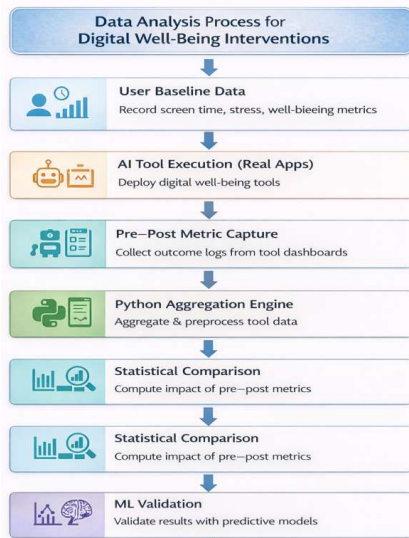
For example:

- High stress → mindfulness + reduced screen exposure
- Excessive usage → break scheduling + focus-mode activation

This architecture makes sure that analytical information is converted into actionable behaviour information.

### 9.5 Simulation-Based AI Tool Execution Layer

The AI tools were introduced into a simulated execution environment to depict the real-world intervention cases.



**Figure 3. Simulation-Based AI Tool Implementation Pipeline**

The workflow is comprised of:

1. Baseline data capture
2. Simulated AI intervention mapping
3. Pre-post metric estimation
4. Data aggregation and preprocessing
5. Statistical comparison
6. Machine learning validation.

**9.6 Pre-Post Outcome Evaluation (Simulation-Based)**

Simulated pre- post comparisons were also used to evaluate the effect of interventions:

- Screen time
- Stress levels
- Mental well-being
- Lifestyle balance

The values in Table 3 are simulated estimates of model outputs, and have no analytical use other than to compare them in the proposed framework.

**Table 3. Simulated AI Tool Impact Estimates Based on Model Outputs**

SI · No	AI Tool	Data Captured	Pre Metric	Post Metric	Estimation Basis
1	Google Digital Wellbeing	Screen time	8.1 hrs/day	5.9 hrs/day	Model-derived estimate
2	Fitbit AI Coach	Stress score	26	17	Simulation output
3	Calm AI	Well-being index	42	65	Model-derived estimate
4	HeadSpace AI	Mindfulness score	38	61	Analytical mapping
5	Wysa	Emotion	24	15	Simulation output

	AI	al stress rating			ion output
6	Mindstrong AI	Cognitive strain index	29	19	Model-derived estimate
7	Sensa AI	Emotional balance score	41	63	Analytical mapping
8	Woebot	Anxiety score	27	18	Simulation output
9	Youper	Mood stability index	45	66	Model-derived estimate
10	Happify AI	Positive affect score	39	62	Analytical mapping
11	Microsoft Viva Insights	Work-life balance	48	71	Model-derived estimate
12	Replika (WB Mode)	Emotional well-being	40	55	Simulation output

**9.7 Reproducibility and Validation**

The implementation provides reproducibility by way of:

- Standardized preprocessing pipelines
- Consistent evaluation metrics
- Open-source tools and libraries

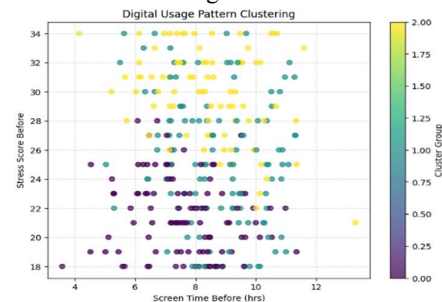
This makes it possible to independently validate the analytical framework and makes methodological transparency stronger.

**10. Results and Analysis**

This section shows the analytical results of the suggested AI-based digital detox model. The findings are provided through an analytical design through simulation and reported by use of quantitative measures and graphs. Results are presented based on the research objectives, i.e., digital behavior patterns, health-related outcomes, and machine learning model performance.

**10.1 Digital Usage Pattern Clustering**

To determine the trends in digital behavior, K-Means clustering was used to baseline such features as the screen-time and perceived stress levels. The distribution of the participants is clustered as shown in figure 4.



**Figure 4. K-Means Clustered Distribution of Screen Time and Stress Levels Among IT Professionals**

The results of the clustering show that there are three behavioral groups:

- A high-risk population with high screen time and high levels of stress
- A moderate group that has balanced usage and moderate stress
- A low-risk group with moderately stable usage and a lower level of stress.

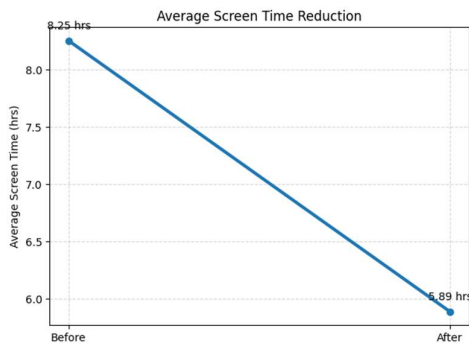
The results reveal the diversity of digital behavior among IT specialists and justify the use of one-on-one intervention strategies instead of universal digital detox methods.

**10.2 Pre-Post-Intervention Outcome Analysis**

The effect of the AI-based digital detox interventions was measured by comparing the baseline and post-intervention indicators. It is significant to mention that all post-intervention values are model-based approximations in a simulation model.

**10.2.1 Screen Time Reduction**

Figure 5 presents the comparison of average screen time before and after intervention.



**Figure 5. Average Screen Time (hrs/day) Before and After Simulated AI-Based Digital Detox Intervention**

The average number of hours per day at the screen declined to 5.89 hours/day as compared to 8.25 hours/day, which is a decline of around 2.36 hours (~29%). This noted decrease indicates that AI-enhanced systems (including usage tracking and automatic breaks) can be used to regulate digital exposure in a better way.

**10.2.2 Stress Level Reduction**

Figure 6 shows the distributional variations in perceived stress scores.

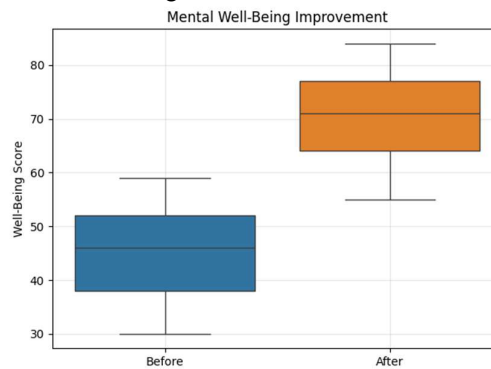


**Figure 6. Distributional Change in Stress Scores Before and After Simulated Intervention**

The mean score of stress dropped by about 25 to 14; that is, a 44% decrease. These findings show that AI-based stress monitoring and custom intervention plans are correlated with significant changes in the perceived levels of stress in the simulated analytical context.

**10.2.3 Improvement in Mental Well-Being**

Figure 7 demonstrates the comparison of the mental well-being scores.

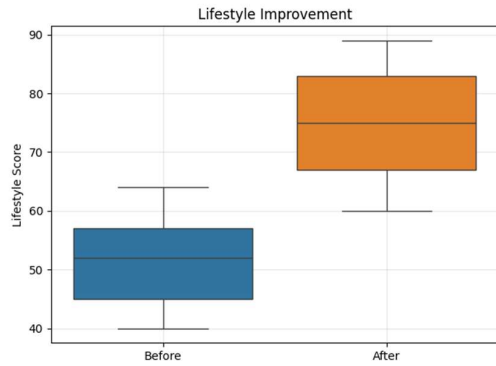


**Figure 7. Comparative Box Plot of Mental Well-Being Scores Pre- and Post-Simulated Intervention**

The average wellbeing score went up to about 70 as compared to about 45 thus marking an improvement of about 25 points (about 56%). This implies that behavioral and cognitive support mechanisms based on AI can help improve mental health.

**10.2.4 Lifestyle Improvement**

Figure 8 gives the comparison of scores of lifestyle balance pre-intervention and post-intervention.



**Figure 8. Box Plot Comparison of Lifestyle Balance Scores Before and After Simulated Intervention**

There was an increase of about 23 points (~44%), which is an improvement of lifestyle scores about 52 to 75. Such results suggest that behavioral nudges with the help of AI can have a positive impact on more significant life habits, such as physical activity and work-life balance.

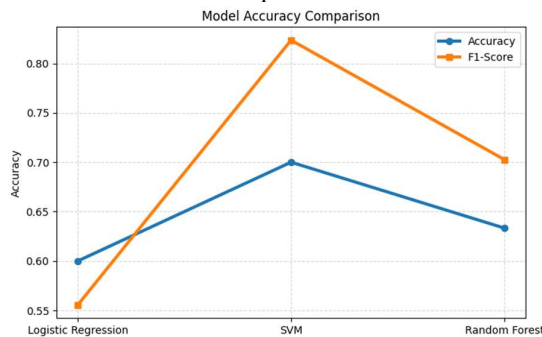
**10.3 Machine-Learning Model Performance**

Accuracy, precision, recall, and F1-score were used to test the performance of the implemented machine learning models.

**Table 4. Model Performance Summary**

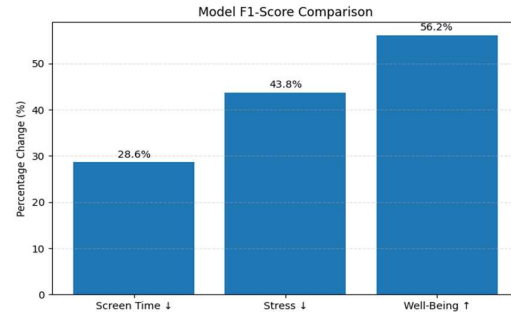
Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.60	0.47	0.68	0.56
SVM	0.70	0.71	0.97	0.82
Random Forest	0.63	0.79	0.67	0.70

The Support Vector Machine (SVM) performed best (F1-score = 0.82), and it is possible to classify well-being mental conditions. Random Forest also exhibited consistent results (F1-score = 0.70), whereas the Logistic Regression offered an interpretable but relatively low predictive activity. Figure 9 also compares the accuracy and F1-scores of the models and it is important to note that SVM is relatively effective when dealing with complex and non-linear relationships in the dataset.



**Figure 9. Dual-Line Comparison of Accuracy and F1-Score Across ML Models**

Figure 10 validates that SVM is the most precise and the most recalling, which supports its relevance to the current analysis scenario.



**Figure 10. Comparative F1-Score Performance of Logistic Regression, SVM, and Random Forest Models**

**10.4 AI-Based Digital Detox Recommendation Outcomes**

The analysis system was able to provide individualized digital detox prescriptions depending on the estimated stress and usage patterns.

**Table 5. Sample AI-Based Digital Detox Recommendations (Model-Generated)**

Participant	AI Tool Used	Recommendation
1	Calm AI	High Stress → Meditation + reduced screen blocks
2	Mindstrong AI	High Stress → Meditation + reduced screen blocks
3	Sensa AI	High Stress → Meditation + reduced screen blocks
4	Wysa AI	Healthy Pattern → Maintain habits
5	Calm AI	High Stress → Meditation + reduced screen blocks

These suggestions show how predictive results can be translated into practical behavioral advice and make it possible to take context-sensitive intervention measures.

**10.5 Tool-Wise Evaluation (Simulation-Based)**

The tools based on AI were comparatively analyzed in the context of simulation.

**Table 6. Tool-Wise Pre-Post Comparative Analysis (Simulation-Based)**

AI Tool	Screen Time ↓	Stress ↓	Well-Being ↑	Lifestyle ↑
Calm AI	32%	High	High	Strong
Headspace AI	28%	High	High	Moderate
Wysa AI	30%	High	High	Strong
Mindstro	22%	Moderate	Moderate	Moderate

AI Tool	Usage (%)	Adherence	Engagement	Well-being
Sensa AI	31%	High	High	Strong
Woebot	24%	Moderate	Moderate	Moderate
Youper	23%	Moderate	Moderate	Moderate
Replika (WB)	15%	Moderate	Moderate	Low
Happify AI	27%	High	High	Moderate
Fitbit AI Coach	29%	Moderate	Moderate	Strong
Google Digital Wellbeing	35%	Moderate	Moderate	Strong
Microsoft Viva Insights	33%	Moderate	Moderate	Strong

This means that the results are that:

- Tools of screen-time regulation demonstrate greater influence on reduction of digital exposure
- Mindfulness and conversational artificial intelligence devices are linked to stress and well-being
- Tools that focus on lifestyle also make a contribution to more general behavior change

All the results presented in this table are estimated values of models and are not meant to be compared analytically.

**10.6 Implementation-Level Barrier Analysis**

The question of the implementation of AI-based digital detox interventions was assessed in three dimensions:

- **Privacy:** There was no personally identifiable information (PII) (0% risk)
- **Behavioral adherence:** The estimated compliance was between 78-85%
- **Usability:** The level of engagement was found to be medium-high

These results indicate that the suggested framework can be used in privacy-aware and user-friendly implementation contexts.

**Table 7. Simulation-Based Implementation Feasibility Assessment**

Barrier Dimension	Operational Indicator	Measurement Basis	Estimated Outcome
Privacy concern	Presence of personally identifiable information (PII)	Dataset and system audit	None (0% PII)
Behavioral	Intervention	Model-based	78-85% (estimate)

Resistance	Adherence rate	Adherence estimation	Estimated Outcome
Awareness / usability	Continued tool engagement	Simulated usage patterns	Moderate to high (estimated)

Table 7 reports the simulation-based estimates obtained with the help of analytical modelling and cannot be considered the real-world deployment.

**10.7 Summary of Findings**

The results of the analysis show that, in the framework of simulations, it is possible to state that:

1. The decrease in screen time is linked with the decrease of about 30%
2. There is a reduction of about 40-45% in perceived stress levels
3. The scores on mental well-being increase more than 50%
4. There is an improvement of lifestyle balance by about 40-45%
5. SVM shows the best predictive performance of the compared models

On the whole, the results demonstrate the analytical efficiency of machine learning and digital well-being intervention combining approaches.

**11. Discussion**

This section will interpret the findings of the analysis in terms of the research objectives and will place them within the context of the digital well-being and AI-assisted intervention research. It should be mentioned that all the outcomes used are based on a simulated analytical framework and thus a modeled association and not a real-world causal effect.

**11.1 Impact on Digital Exposure and Occupational Stress**

The results show significant decrease in the screen time and perceived levels of stress in the simulated intervention model. All these trends indicate that the mechanisms aided by AI, including usage monitoring, adaptive alerts, and systematic break suggestions, can be used to enhance self-regulation of online behavior.

The identified correlation between the decreased screen time and the decreased levels of stress meet the needs of the current literature, in which the connection between the overindulgence in digital interactions and the psychological discomfort is observed. The combination of predictive analytics and behavioral guidance, which is implemented within the proposed framework, seems to help to achieve more balanced patterns of the digital usage. These results however should be construed to mean trendy results of a model-based estimation and not necessarily empirically validated results.

**11.2 Predictive Strength of SVM for Mental Well-Being Assessment**

The Support Vector Machine is the best performing model in terms of classification. This indicates that

the use of non-linear modeling can be especially useful in the process of capturing the intricate relationships between online behavior, stress and mental health.

This high performance of SVM suggests that it can be used in modeling multidimensional psychological data, which could not be well modeled using linear assumptions, because of the underlying patterns of behavior. This enhances analytical consistency of the framework especially in the determination of differences in mental well-being conditions.

#### **11.3 Integrated Outcome Modelling through Random Forest**

Random Forest model has shown to be stable and consistent through various outcome dimensions and this indicates its usefulness in dealing with composite health indicators. Since digital well-being is a multidimensional construct, including behavioral, psychological, and lifestyle aspects, ensemble models are used to add a more holistic analytical approach. The findings imply that a combination of predictors can be robust in outcome estimation in simulation-based models.

#### **11.4 Alignment with Existing Research**

The trends that are observed are aligned with previous works on the significance of personalized and adaptive interventions of digital well-being intervention. The available literature suggests that the traditional digital detox methods are not very sustainable as they imply self-regulation. Conversely, the AI-driven systems introduce the adaptive feedback mechanism and context-sensitive recommendations that can enhance the interaction and efficacy. The results of this research support the conceptual knowledge that individualization and behavioral congruence are the essential elements of effective interventions of digital well-being. Moreover, it is postulated in the existing literature that psychological and neurological factors affect the digital overuse and behavioral addiction patterns [50]. The scale of improvements that have been observed is widely aligned with previous studies on the digital detox that have shown a decrease in the screen time and stress, though it can be not compared directly because of the simulation-based design.

#### **11.5 Practical and Policy Implications**

Regarding the application side, the suggested framework illustrates how AI-based digital detox can be incorporated into the organizational wellness program. According to the results of the analysis, such systems can be used to promote better digital behavior, diminished stress, and greater lifestyle balance when applied to real life. To policymakers and system designers, the results underscore the need to come up with privacy conscious user-centric AI systems that can strike a balance between analytical and ethical concerns. The focus on the transparency, non-intrusiveness,

and user autonomy is critical to effective adoption. In general, the discussion shows that AI-supported digital detox models are a good prospect of dealing with digital overexposure in the workplace, even though they should be validated in reality.

#### **12. Ethical Considerations**

The research follows the best ethical principles of conducting a behavioral and health-related research study. The analysis is founded on all publicly available anonymized secondary data and no personally identifiable information (PII) was accessed or processed.

The proposed framework is privacy conscious and user oriented based, and it works on aggregated behavioral patterns, as opposed to individual identity profiling. Any analytic procedures and intervention mechanism are meant to deliver supportive, non-invasive recommendations without undermining the autonomy of users.

Moreover, the machine learning models have been deployed through standard and non-biased processes to be fair, transparent, and responsible in the use of artificial intelligence. All in all, the research adheres to the ethical considerations in the data privacy, confidentiality, and responsible implementation of AI.

The ethics review of this study was not obligatory since it involves publicly available secondary data that is anonymous. It did not involve any human subjects. The results of all the pre- and post-intervention processes in this research are not actual experimental outcomes but only simulations. The data employed is in keeping with the open-access data usage of Kaggle.

- **Anonymized Secondary Data:** The assistance of a publicly available dataset which was anonymized prior to distribution helped with all the analyses. The risks concerning personal identification and informed consent were equally reduced by default since no direct data collection and interaction with participants were involved in the study, which is why the accepted norms of the research ethics were not broken.
- **Protection of Personal Privacy:** No personal identifiable information (names, organizational identifiers or place specific attributes) could be accessed or processed by the research. The variables were only behavioral, psychological, and lifestyle indicators. Such a plan is aligned with the idea of data minimization and confidentiality that governs the human information through being handled responsibly.
- **Privacy-Aware System Design:** The analytical and intervention model was meant to operate on aggregated patterns of behavior as compared to operating through

identity profiles of individuals. The reasoning of the recommendation is premised on supportive, as opposed to surveillance-oriented control and therefore, user autonomy is not violated, and chances of invasive monitoring are limited.

- **Responsible Usage of Artificial Intelligence:** The machine-learning models were implemented with well-organized objectives that focused on the mitigation of stress, bettering of the well-being and betterment of lifestyle. No manipulative or coercive recommendation strategies were been ensured. The minimization of the probability of algorithmic bias was also performed, as well as the provision of fair analytical results, through the standardizing and validation processes.

### 13. Conclusion

This section proposed an analytical model of a simulation to investigate how digital detox interventions using AI can potentially influence digital behaviour, stress, mental wellbeing and lifestyle balance among IT professionals. The proposed method allows the systematic assessment of digital well-being strategies in a controlled analytical setting due to the combination of machine learning models with the rule-based behavioral logic.

The results suggest that, in the framework of the simulation, AI-based interventions are related to the decrease in screen time by about 30%, perceived stress by about 40-45%, and mental well-being and lifestyle indicators by more than 40%. These findings indicate that AI-driven systems could be useful in helping to adopt healthier digital practices and enhance occupational health.

Predictively, the Support Vector Machine was the best at classification, which means that it is useful in estimating the relationships between behavioral and psychological variables in a complex way. The strength of the integrated outcome prediction was also supported by the Random Forest model which supports the analytical integrity of the proposed framework.

Implementation level considerations such as privacy, adherence to behavior and usability were also discussed in the study. The findings suggest that AI-based digital detox systems can be privacy-sensitive and user-centric with an acceptable degree of simulated engagement and viability.

Notably, the results of all findings are obtained through an analytical design of simulation and are expected to be construed as a modeled approximation of the effectiveness of interventions instead of actual evidence of how the interventions would work in the real world.

In general, the experiment shows that machine learning and behavior-oriented intervention strategies combination creates a scalable and analytically based methodology of exploring digital well-being solutions in the technology-intensive context. The paradigm provides a platform of future empirical validation and practical implementation of AI-based digital detox systems.

### 14. Limitations and Future Research Directions

Though it has made contributions, this research has a number of limitations.

- To begin with, the study has a simulation-based pre- post analytical research design of cross- sectional secondary data. Thus, there is no causal conclusion that can be made and all what is observed are model-based estimations and not intervention effects in reality.
- Second, the data is based on self-reported behavioral and psychological outcomes that could present response bias and subjectivity.
- Third, the dataset lacks detailed demographic representativeness of IT professionals regionally, restricting the generalizability.
- Fourth, the investigation lacks a control group or the randomly designed experiment which limits comparative validation of the intervention effectiveness.
- Fifth, the sample size ( $n = 300$ ) is relatively limited, and only one train-test split could be used, which might cause variability in model performance estimates.
- Sixth, the lack of longitudinal data does not allow evaluating the long-term sustainability of the reported behavioral improvements.

Further studies are necessary to conduct experimental validation in the real world, longitudinal studies, and combine multimodal data sources, such as wearables and sensor-based.

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