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IoT-Enabled Intelligent Health Care Screen System for Long-Time Screen Users †

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Abstract: With the rapid rise in technological advancements, health can be tracked and monitored in multiple ways. Tracking and monitoring healthcare gives the option to give precise interventions to people, enabling them to focus more on healthier lifestyles by minimising health issues concerning long screen time. Artificial Intelligence (AI) techniques like the Large Language Model (LLM) technology enable intelligent smart assistants to be used on mobile devices and in other cases. The proposed system uses the power of IoT and LLMs to create a virtual personal assistant for long-time screen users by monitoring their health parameters with various sensors for real-time monitoring of the seating posture, heartbeat, stress level, motion tracking eye movement, etc., to constantly track and give necessary advice and make sure that their vitals are expected and in safety parameters. The intelligent system combines the power of AI and Natural Language Processing (NLP) to build a virtual assistant embedded into the screens of mobile devices, laptops, desktops and other screen devices, which employees across the various workspaces use. The intelligent screen, with the integration to multiple sensors, tracks and monitors the users' vitals along with various other required health parameters and alerts them to take breaks, have water, refresh and ensure that the users stay healthy while using the system for work. These systems also suggest the required exercises for the eyes, head and other body parts. The proposed smart system is supported by user recognition to identify the current user and suggests advisory actions accordingly. The system also adapts and ensures the users get proper relaxation and focus when using the system, providing a flexible and personalised experience. The intelligent screen system monitors and improves the health of the employees who have to work for a long time, thereby enhancing the productivity and concentration of the employees in various organisations.

Keywords: intelligent system; health care; vital; intelligent screen; virtual personal assistant; smart screen

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1. Introduction

The Internet of Things (IoT) is transforming people's lives in many ways in today's technology-driven world, where people spend most of their time in front of screens. Spending countless hours in front of screens also has adverse health challenges [1]. Technological advancements have facilitated the interconnection of various devices and sensors, enhancing personal care and enabling the design of effective health management systems that support innovative treatment plans and improve quality of life. Most of the time, people spend time in their workspace, and tracking and supporting them to monitor and focus on their health is required to have a better and stronger workforce [2,3]. As technological advancements have grown beyond the limits, numerous benefits and ways they can be associated with lives have also been devised. With the users' health as a primary goal, smart screens are required to assist those on screens by monitoring and advising them to take breaks and take necessary precautions to care for their health.

As the lifestyle of people has changed to a heavy dependence on screens, this started affecting the health of people; health issues like eye strain, back pain and even cardiovascular problems are now common among people. Relaxing movements are required for people accustomed to long screen time for their work. Many health risks are associated with long-time screen use [4,5]. The health of these people is dependent on various factors, including measurable and monitored parameters [6]. The research explores the possibility and checks the stability of the application of such a system where the users' health is also monitored; appropriate activities of remedies are recommended for their well-being.

The evolution of AI and its derivatives, particularly Large Language Models (LLMs), has opened exciting possibilities for addressing various challenges and improving Human-Computer Interaction (HCI). The HCI helps address the challenges and improve people's lives. With their ability to understand and generate human-like language, LLMs can potentially power intelligent virtual assistants to seamlessly support users and assist them in their daily lives [7,8]. The use of AI and advanced technology frameworks like LLMs helps the creation of virtual assistants for communication with the power of Natural Language Processing (NLP), which can generate personally tailored advice and guidance [9]. This can be reminders to take breaks, stretch, drink water, or suggestions to reduce eye strain and improve posture, which are interactive systems for proactive health management.

2. Methods

The intelligent screen system is designed to capture user behaviour from various sensors in the workspace and workstation. The screen can also be integrated with various wearable devices, including smart watches and such devices, which capture the users' data and pass it to the data analytics engine. The data analytics engine processes, stores, and analyses the data and information from the sensors and oversees user behaviour. The health parameters and the emotional changes of the user are also captured with the different sensory devices interconnected over the private network, set up to be part of the smart screen system. Figure 1 represents the overall architecture of the smart screen system, which is designed for long-time screen users to ensure that their health is monitored and recommended actions are given to them with regular interventions using a voice-based interactive assistant in their workspace screen.

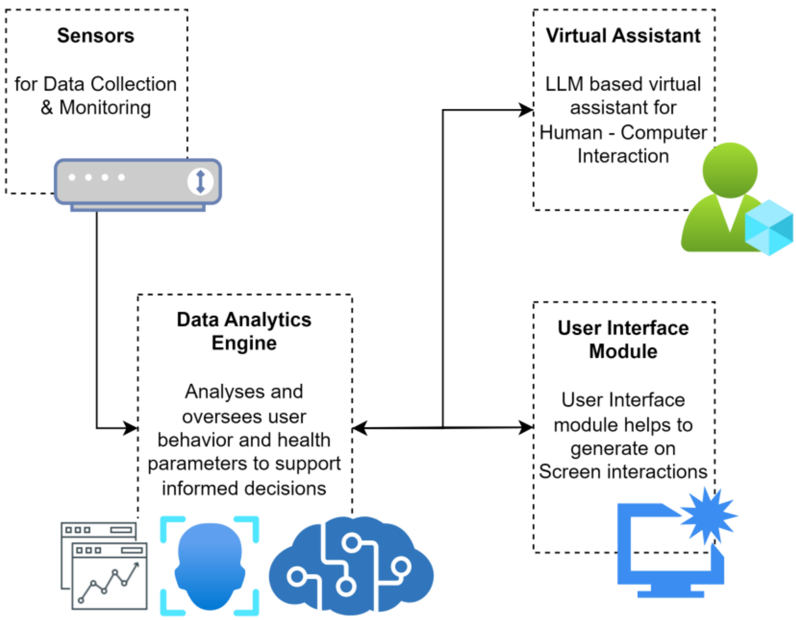

Figure 1. The architecture of Smart Screen System for long-time screen users.

The data analytics engine tracks and identifies the person using the workspace, identifies his preferences and presets the virtual assistant and user interface modules with appropriate settings tailored for each user. The virtual assistant is designed and customised with NLP and uses the power of LLMs to converse with the users. The users get tailored messages that are fine-tuned for their well-being. Self-supervised learning algorithms employed in the analytics engine track user behaviour in real-time with the support of various sensors to identify the effects of suggestions given to streamlining user expectations [10].

2.1. Sensor Data Collection & Processing

Various sensors track and extract the required data from the user and his behaviour and send it for processing. The sensor and sensor control unit performs the following major tasks:

- Interface between sensors for heart rate monitor, posture sensor, eye tracker, etc.
- Ensuring and aggregating Real-time data acquisition and processing.
- Data filtering and noise reduction.
- User behaviour tracking and detection.

The rich set of sensors and their integration is required to ensure that the system works effectively and gives tailored messages and recommendations to the users. Figure 2 represents the collective list of sensors in the system architecture, which supports gathering various parameters related to the user work environment. The sensor-data collection unit collects and aggregates the data for the system and passes it to the analytics layer.

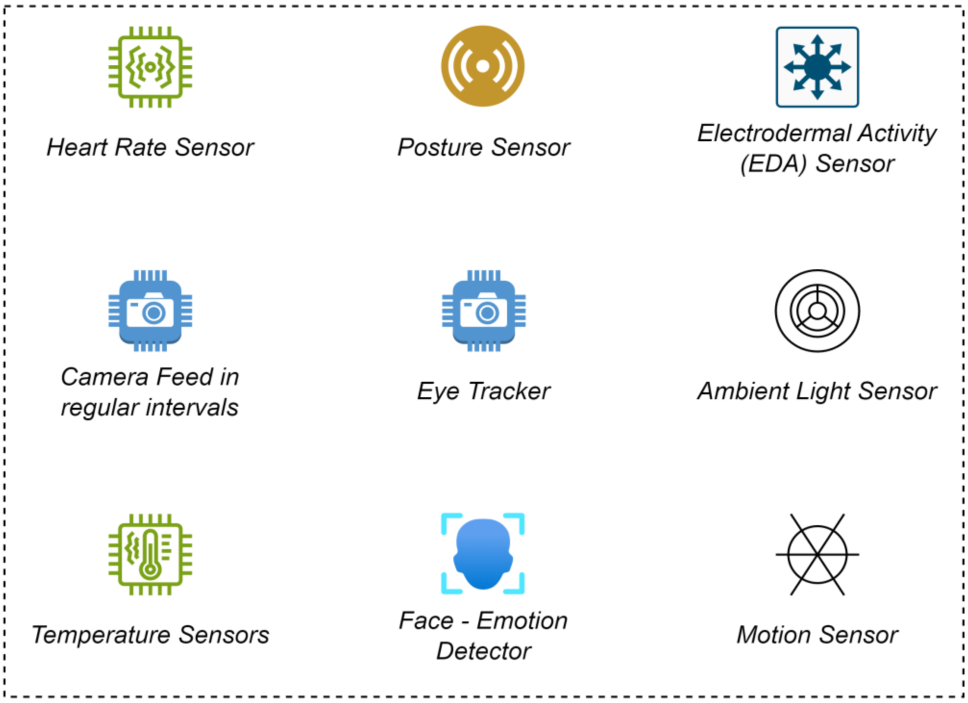

Figure 2. Sensors used in the smart screen system.

The smart screen system integrates advanced sensors specifically selected for monitoring different health parameters of long-time screen users. Various sensors that will be part of the system include the following: these are some of the functions of these sensors in the system.

- Heart Rate Sensor (MAX30100, Maxim Integrated Products, US)—Helps to track the heart rate and its variation; monitoring heart rate and its variability will help to track stress levels and cardiovascular health. The sensor also helps to measure the blood oxygen levels and identifies the freshness in the workspace.
- Posture Sensor—The Posture sensor is a combination of multiple pressure sensors (FlexiForce A401, Altera Corporation, US) and an Inertial Measurement Unit (IMU) (MPU-6050, TDK Electronics, India) to monitor head and shoulder angles. These sensors track the user's sitting posture and identify the potential problems and risks associated with ergonomics. Posture sensors will combine pressure sensors and camera-based pose estimation techniques.
- Camera Feed—The live camera feed tracks the user's emotional status, estimates the seating posture, and tracks the eye movement and time spent starting the screen. All these estimations and validations are done on the images and video footage obtained from the camera and processed by CNN models to extract features.
- Eye Tracker (Tobii Eye Tracker 4C, Element14, India)—Tracks eye movements and detects signs of eye strain; it also monitors the blinking rate, fixation duration, pupil dilation, etc., from the user's face. These are also done with the support of the camera and ML models associated with the process.
- Temperature Sensor (DHT11, Element14, India)—Measures the workspace temperature, body temperature and seat temperature to analyse the comfort level of the posture and the workspace balance.
- Face & Emotion detector—The face of the user and the emotions while using the application or screens are tracked. Tracking the face, the time the face is in front of the screen, and the emotional status during this time are also extracted with the help of ML and DL algorithms from the video feed and processed with CNN models to extract relevant features.
- Electrodermal Activity Sensor (Shimmer3 GSR, Element14, India)—This sensor is used to measure skin conductance as an additional indicator of the stress and emotional status of the user.
- Ambient Light Sensor (TSL2561, TAOS, US)—This sensor measures the surrounding light levels, adjusts screen brightness, and reduces eye strain. The sensor will also help understand the change in eye movements and facial expressions based on the light intensity in the workspace.
- Motion Sensor (HC SR501, Element14, India)—This sensor detects and tracks the user's movements, identifies the inactive time, and helps to remind the users to take breaks and change positions to have better body movements to enhance comfort and improve productivity.

The data from these sensors is processed through a multi-stage pipeline that involves noise reduction, feature extraction, and data fusion. A real-time data filtering process using Kalman filters and moving average filters is implemented to remove artefacts caused by motion or sudden environmental changes. These are some of the significant sensors and sensory groups designed to provide significant insights into the working conditions of employees working with screens for a long time. The data function techniques are applied to various sensors to ensure that the data the sensor generates is proper and gives the proper interpretations.

The placement and integration of sensors play a critical role in ensuring accurate data capture and minimising interference from environmental factors. The following outlines the sensor placement strategy used in the proposed system. All the sensors are placed in different places, either embedded on the laptop or systems that the user uses or for the seating setting in the workspace, without interfering and hindering the regular movement of the employee in the workspace. The placement of some of the sensors is as described below:

- Heart Rate Sensor—Mounted on a wristband or wearable that maintains direct skin contact, positioned to avoid disruptions from wrist movements.
- Posture Sensors—Integrated into ergonomic seating arrangements, with pressure sensors distributed across the seat and backrest to detect weight shifts and slouching.
- Eye Tracker—Attached to the top bezel of the screen to ensure an unobstructed view of the user's eyes. Positioned at a fixed distance to maintain accuracy across different users.
- Temperature Sensor—Embedded within the screen frame to measure ambient temperature and identify user comfort levels.
- EDA Sensor—Placed on the non-dominant wrist to reduce motion artefacts and interference during typing activities.

Along with these sensors, various other data points are also combined for the analysis, which include:

- Internet usage
- Time spent on mobiles
- The tone of the communication
- Login—Logout time
- Typing speed
- Scrolling speed

Various factors are measured with the help of single sensors, a combination of sensors, and other AI-based software solutions, as well as with the help of monitoring the usage statistics of interconnected devices. The efficiency and productivity of the people can also be monitored and improved with the support of this personal assistant. Hence, the personal assistant can understand the surroundings and what the person is going through before making informed suggestions to the users.

2.2. Data Analytics Engine

The data from the sensors, sensory arrays, and associated devices are sent to the analytics engine, from which the data is first processed and finetuned for effective storage in a local centralised data store. The data stored in the data store is then effectively processed and analysed with the help of various Machine Learning (ML) and Deep Learning (DL) algorithms. Deep learning algorithms are used for pattern mining and feature extraction, whereas machine learning algorithms are used to support informed decision-making. The engine is designed in such a way that it can distinguish between the users and identify their behaviours. The various components of the Data Analytics engine are represented in Figure 3, where the data flow and the communication between various components are represented.

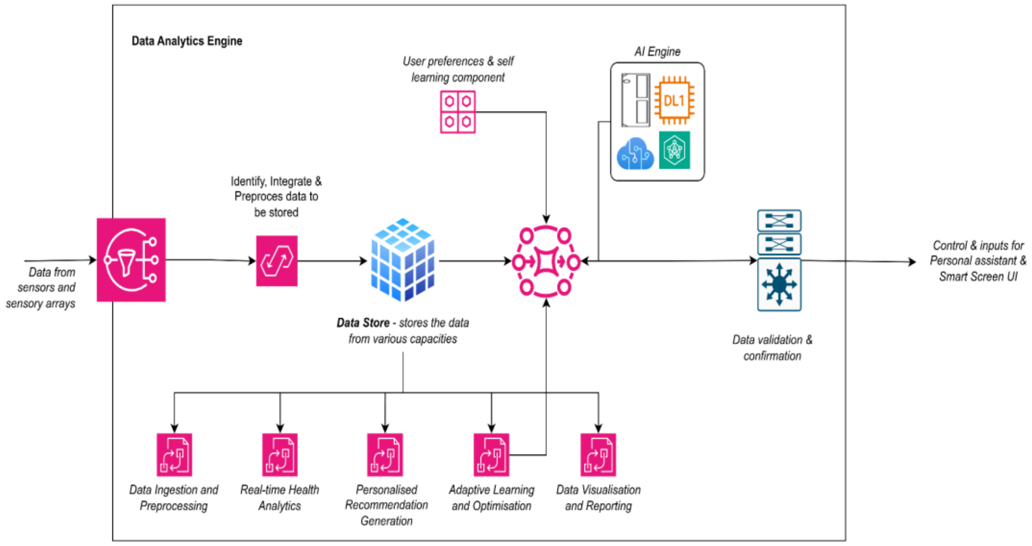

Figure 3. Components of the Data Analytics Engine.

The data analytics engine takes the live data from various sensors and sensory arrays and places it in the data store; the significant steps that these data undergo as part of the analysis and decision-making engine are as follows:

- Data ingestion and preprocessing—Analyses, verifies and streamlines the data from various sensors and sensory arrays stored in the data store. This process also verifies the data with the user's health database and medical history to identify and record abnormalities. Required data filtering, cleaning and other processes are part of this step to verify that the actual data is stored in the database.
- Real-time health analytics—Keeps track of health-related parameters from the various sensors. This keeps track of anomalies and reports to users on the steps they should take. With the help of DL algorithms, the system captures the various parameters, and then, using ML algorithms, the system will predict the user's health.
- Personalised Recommendation Generation—This analytical engine handles personalised health tracking and reports. The system uses a rule-based system to trigger the actions and recommendations for the other part of the system to get the users to care for their health.
- Adaptive Learning and Optimization—This part of the analytical engine manages the feedback from the user based on the recommendations made to them and self-learns the changes that the user has to undergo for each of the changes. The adaptive learning system is essential in the recommendations of actions for the identified stages.
- Data visualisation and reporting—This section focuses on generating reports for the user, based on which the user can finetune the system settings to tailor to the needs of the individual.

The data analytics engine employs supervised and unsupervised ML algorithms for processing the data, pattern recognition and decision-making. The ML algorithms used for implementing the data analysis engine and their role in the engine are described below:

- Random Forest (RF) Classifier—The RF classifier helps in the effective classification of the seating posture of the users from the sensor data, which includes the head and shoulder angles. RF uses the decision trees to identify the non-linear relationships between different ergonomic features. RF model is implemented to handle the possibility of noisy sensor data.
- Support Vector Machine (SVM)—SVM detects the user's stress. SVM makes the stress classification based on the Electrodermal Activity and the heart rate variability data.

- Convolutional Neural Network (CNN)—CNN is applied to extract data from the live camera feed to track the user's facial emotions, eye movements, and posture. The CNN model extracts spatial features from video frames and predicts eye strain and emotional status.
- K-Means Clustering—K-Means clustering algorithm groups the users based on behaviour patterns and identifies the recommendations based on screen time, typing speed and activity breaks.
- Long Short-Term Memory (LSTM) Networks—LSTM is implemented to track the dependencies in user behaviour while continuously monitoring health trends over time. LSTM could detect abnormalities over time and help recommend breaks and other activities based on user interactions.

Each of these algorithms was identified based on the strengths of the algorithms for the application based on literature and experiments carried out in the design and development of the prototype. The model performance and accuracy were validated using standard evaluation metrics such as precision, recall, and F1-score to ensure reliability and effectiveness in diverse work environments. The results and recommendations generated from the ML algorithms from the analytical engine are converted to signals passed to the virtual assistant and the user interface modules to communicate with the users and ensure that the users benefit from the recommendations. The system understands the users and makes tailored recommendations based on the user history and preferences set and identified from actions.

2.3. Virtual Assistant

A virtual assistant is designed to interact with the users and communicate the suggestions and feedback the data analytics engine produces. The virtual assistant is powered by NLP, which tries to understand the user's emotional and personal responses and provides feedback to the users. The major components and its role in the virtual assistant include the following:

- Natural Language Understanding (NLU)—The role of NUL is to accurately identify the user's intent from their spoken query and responses [11], which include queries like health information, break reminders, seeking exercise suggestions, etc. Track and extract information from the entities associated, maintain context and set the appropriate context for the conversations.
- Natural Language Generation (NLG)—The NLG engine formulates clear, concise, and contextually relevant responses based on the user's intent and system recommendations. Generate the conversation responses according to the user's preferences and communication styles [12]. Enhance and track user engagement and make changes in the style of interventions.
- Dialogue Management—Responsible for maintaining natural, engaging conversations, tracking the conversation flow, and adapting to changes when interruptions occur during the conversations [13]. The change and track of the flow are maintained so that the user is not offended by the system responses by retaining relevant information from previous interactions to provide contextually appropriate responses.

The virtual assistant integrates and interacts with the data analytics engine to engage with the user and provide appropriate recommendations. This includes extracting relevant information from the data store, including the health parameters and relevant previous history. The system will be customised to assist the users with empathetic responses and emotional awareness to promote a supportive user experience. The virtual assistant uses a combination of NLP models and reinforcement learning to optimise user interactions. The core NLP model is a Transformer-based architecture similar to Bidirectional Encoder Representations from Transformers (BERT) for intent detection and context understanding. Reinforcement learning algorithms like Q-learning are applied to personalise responses based on user preferences and engagement patterns, ensuring the assistant evolves to provide more relevant suggestions. The virtual assistant constantly works with the data analysis engine and the user interface module to provide an immersive experience to the users.

2.4. User Interface Module

The user interface module is another component of the smart screen system, which acts as an interface between the users and their responses. The user interface module supports the design and development of UI components that pop up on the screens, communicate with the user by giving recommendations, and allow the user to customise the system settings according to their comfort. The user interface module will have a dashboard as a central hub for displaying real-time health metrics, personalised recommendations, and system notifications. The virtual assistant interface facilitates interaction with the LLM-powered virtual agent [14,15]. The users will have access to tracked data and identify the abnormalities the system recommends. The UI components are designed to include gamification elements and a reward system that motivates the user to adhere to the health recommendations. Excellent care has been taken to minimise the disturbance and impact on the storage and performance of the workspace with the inclusion of the intelligent system that takes up more computation and memory space; tailored customisation options given to the users will help them to decide the local storage and computational requirements which they opt for.

3. Results and Discussion

The system was designed and tested on 30 participants from diverse ages and ethnicities. The aim was to understand the effectiveness of the proposed system in their workspaces. During the data collection process for the study, the participants were equipped with the full sensor suite, and we collected data from 30 participants during 8-h work sessions. The data from the experimental setup is stored in a 10-s interval period. Table 1 shows the range of participants for which the study was conducted and the gender diversity of the study.

Table 1. Count of participants in various groups.

Category	Age Range	Count of Participants	Male	Female
School	Up to 17 Years	7	3	4
College	18–25 Years	9	4	5
Working	21–60 Years	10	6	4
Others	61 and Above	4	2	2

Each data sample stored has detected, computed and processed data attributes that include the following: heart rate, eye movements (blink rate, pupil dilation), posture metrics (head angle, shoulder angle, back angle), emotional state (stress level, facial expression detection), environmental conditions (ambient temperature, ambient light), and user-specific characteristics (gender, age, job role, distance travelled from home to office, calories consumed), Internet usage, Time spent on mobiles, The tone of the communication, Typing speed, Scrolling speed are also captured regularly. The heart rate sensor and EDA sensor were calibrated at the beginning of each session to ensure accurate baseline measurements. Posture data was captured using pressure sensors embedded in an ergonomic office chair, and eye movement data was tracked using the Tobii Eye Tracker 4C mounted on a 24-inch monitor. Data preprocessing involved a two-step noise reduction process using a Butterworth filter and a Savitzky-Golay smoothing algorithm. Anomalies were detected using Isolation Forest models, and health recommendations were generated based on predefined threshold values for each health metric.

Posture Score of the user is calculated by the Equation (1):

$$\text{Posture Score} = w1 * \text{Head Angle} + w2 * \text{Shoulder Angle} + w3 * \text{Back Angle} \quad (1)$$

where:

- w1, w2 and w3 are weights assigned to each postural parameter based on relative importance.
- Head Angle, Shoulder Angle, and Back Angle are measured in degrees and compared to ideal ergonomic ranges.

Table 2 (Tables 2a,b), shows the dataset snapshot captured for the participants on the various data points considered for the study. The data points are extracted and computed from the readings from multiple combinations of sensors and data pre-processing steps. The data was captured using various sensors and processed into a dataset using the above mentioned parameters. The system has computed and stored the data for participants from different age groups and genders. The participant's user behaviour tends to spend more time on the screens. A detailed study of each of the parameters and their impact is to be analysed for the adjustments and preparation of the intelligent engine for the designed system.

Table 2. Dataset snapshot. (**a**) Sample Dataset Snapshot Part 1; (**b**) Sample Dataset Snapshot Part 2.

(a)

Category	Gender	Time (s)	Heart Rate (bpm)	Blink Rate (blink/min)	Pupil Dilation (mm)	Head Angle (Â°)	Shoulder Angle (Â°)	Back Angle (Â°)	Stress Level (1–10)
School	Male	0	72.49	24.26	4.33	4.97	11.56	4.68	8
School	Male	10	83.77	10.01	4.98	5.44	16.12	0.21	9
School	Male	20	66.81	19.28	3.46	14.58	14.67	25.80	7
School	Male	30	71.09	11.47	4.21	1.00	11.22	14.86	3
School	Female	0	69.20	15.69	4.93	−1.58	12.96	27.55	6
School	Female	10	72.16	17.41	4.57	−1.62	11.74	21.36	8
School	Female	20	68.83	19.21	3.59	4.43	17.38	24.19	3
School	Female	30	78.63	12.51	4.14	14.79	10.73	2.31	3
College	Male	0	72.94	16.83	3.54	8.26	11.35	5.93	10
College	Male	10	67.54	15.88	2.91	8.36	12.09	1.76	1
College	Male	20	70.91	17.95	4.20	4.82	11.48	5.16	3
College	Male	30	80.10	18.80	4.57	−8.00	14.77	18.90	4
College	Female	0	71.59	16.61	4.64	7.11	18.82	6.11	4
College	Female	10	79.96	13.12	3.01	−5.26	11.26	9.33	9
College	Female	20	71.73	18.80	2.76	8.25	13.87	23.53	10
College	Female	30	76.24	18.29	2.79	−6.85	15.30	8.07	8
Working	Male	0	82.75	17.06	4.70	4.65	16.74	24.13	8
Working	Male	10	84.39	24.39	3.39	−8.35	11.67	29.78	10
Working	Male	20	70.85	11.19	3.72	−2.14	12.02	28.58	9
Working	Male	30	68.46	15.17	2.65	−3.25	17.68	26.55	1
Working	Female	0	65.88	18.50	3.50	9.30	10.38	12.05	10
Working	Female	10	84.58	20.68	3.73	11.43	11.04	13.48	5
Working	Female	20	67.16	17.60	2.71	14.24	10.39	22.61	8
Working	Female	30	71.08	16.75	3.86	−7.49	19.32	11.24	3
Others	Male	0	76.48	10.41	3.16	7.76	16.78	10.60	3
Others	Male	10	78.93	18.09	3.78	−6.02	13.72	20.18	8
Others	Male	20	66.25	12.69	2.81	12.87	11.40	16.13	8
Others	Male	30	83.16	10.88	3.97	4.04	16.60	25.00	8
Others	Female	0	65.59	15.71	3.52	2.13	16.69	11.09	4
Others	Female	10	70.54	15.04	4.10	−5.23	19.13	13.98	2
Others	Female	20	79.12	15.90	3.18	−9.92	17.20	25.01	7
Others	Female	30	78.39	12.07	4.18	14.48	15.32	6.42	7

(b)

Facial Expression Detection	Ambient Temperature (Â°C)	Ambient Light (lux)	Age (years)	Distance Travelled (km)	Calories Consumed (kcal)	Internet Usage (MB)	Time Spent on Mobiles (minutes)	Tone of Communication	Typing Speed (WPM)	Scrolling Speed (scroll/min)
Positive	22.81	383.23	15	2.64	2583.00	451.83	27.66	Positive	85.61	28.42
Positive	22.20	259.94	13	29.24	1849.16	1154.20	14.37	Positive	61.80	49.75
Positive	21.60	105.31	10	29.00	2712.60	1472.24	6.21	Neutral	91.30	25.46
Negative	21.13	172.89	13	10.04	2280.10	1817.55	16.65	Positive	89.84	28.53
Positive	24.08	495.23	11	24.83	2188.90	892.95	11.93	Positive	88.82	44.59
Negative	18.81	195.95	13	27.26	2609.51	1947.49	15.41	Positive	93.64	31.36
Positive	19.01	370.47	11	10.13	1505.73	1497.91	20.92	Neutral	79.58	10.76
Negative	24.93	186.21	16	7.17	1549.78	129.45	53.96	Negative	93.28	19.13
Negative	20.10	310.10	19	12.64	2007.13	459.62	17.34	Positive	79.49	37.46
Positive	22.76	448.77	20	4.38	1881.39	1113.66	56.99	Neutral	38.50	39.28
Positive	24.96	248.62	22	3.34	2909.35	704.15	5.76	Negative	70.54	45.82
Negative	20.46	178.08	22	4.61	2812.70	1100.19	35.03	Positive	93.70	47.46
Negative	18.48	455.44	23	13.00	1948.87	1211.85	24.67	Neutral	34.39	20.31
Positive	24.10	302.05	19	26.74	1705.96	1527.26	5.05	Neutral	43.64	21.30
Negative	23.77	476.51	18	15.94	2661.98	485.08	49.24	Neutral	81.45	13.72
Positive	23.25	179.28	22	16.64	2953.22	1368.30	53.91	Negative	43.62	37.45
Positive	20.68	426.34	35	25.53	1673.28	651.96	10.28	Neutral	78.96	35.13
Positive	20.31	202.80	29	20.83	2688.07	1353.44	32.67	Neutral	52.78	14.44
Negative	19.40	179.46	23	3.03	2516.42	287.18	30.09	Negative	60.59	34.31

Positive	21.76	449.43	25	20.45	2771.03	1165.25	27.56	Negative	44.55	28.56
Positive	20.33	151.53	40	20.63	2512.57	518.61	47.54	Neutral	95.31	16.22
Positive	24.11	304.32	39	28.54	2009.29	848.82	44.96	Negative	86.40	36.89
Negative	21.78	390.78	37	9.15	2865.33	1237.16	24.86	Positive	97.11	11.03
Negative	21.24	184.23	55	2.61	1926.81	810.80	35.02	Neutral	96.80	28.00
Negative	19.89	284.51	61	10.88	2932.00	717.78	8.41	Neutral	48.34	41.58
Positive	24.53	220.16	61	11.17	1862.20	1302.16	52.19	Negative	31.93	22.35
Negative	22.35	139.62	65	24.32	2305.51	1684.61	22.25	Negative	51.91	40.62
Positive	19.75	393.69	65	19.18	2330.19	425.11	15.76	Negative	79.94	47.79
Positive	25.08	492.42	67	16.85	2012.55	1783.90	40.84	Negative	92.26	40.62
Negative	24.12	106.54	68	14.62	1614.91	1336.59	28.32	Neutral	82.62	25.66
Positive	22.51	191.07	62	14.07	1618.14	373.90	17.54	Negative	30.32	38.43
Negative	22.10	313.26	67	2.43	1704.58	1876.30	8.85	Negative	58.54	33.18

However, the scope of the current study and its implementation was limited to a few attributes, which include Heart Rate, Eye Blink Rate, Posture Score, and Stress Levels. Table 3 shows the trend observed from the gathered data that helped to infer from the usage and tracking of the user statistics, as well as the interventions provided for the participants during the usage of the system. The table shows the level before and after the recommendations provided to the participants and the percentage of improvement in the metrics for a subject. The interventions given to the participants included the recommendations for taking breaks, listening to music, speaking with a colleague, turning on lights, turning off lights, applying curtains, and opening up windows. These interventions were based on the preliminary study done to implement the project.

The results demonstrated that users significantly benefited from an intelligent system that recommended actions to manage stress and enhance their workspace experience. The study conducted on parameters (heart rate, eye blink rate, posture score, and stress level) has proven the interventions by giving suggestions to the users, which helped them to improve their overall score and satisfaction, ensuring their time spent in the workspace.

Table 3. Impact on health metrics.

Metric	Baseline (Pre-Intervention)	Post-Intervention	Improvement (%)	p-Value
Average Heart Rate	75 bpm	70 bpm	6.67%	<0.05
Eye Blink Rate	15 blinks/min	18 blinks/min	20%	<0.01
Posture Score	65 (out of 100)	75 (out of 100)	15.38%	<0.05
Self-Reported Stress Level	6 (on a scale of 1–10)	4 (on a scale of 1–10)	33.33%	<0.01

A user satisfaction survey has been conducted to evaluate and validate the findings and implementations of the proposed system. Table 4 shows the overall satisfaction based on the study conducted for the system users. An intelligent assistant system to assist them in caring for their health during work time has helped their overall experience. Table 4 shows the summary of the user satisfaction survey.

Table 4. User satisfaction survey results.

Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
The system helped me take regular breaks.	0.7	0.25	0.05	0	0
The system improved my posture.	0.6	0.3	0.1	0	0
The system reduced my eye strain.	0.65	0.25	0.1	0	0
I recommend this system to others.	0.8	0.15	0.05	0	0

The results demonstrate the efficacy of the intelligent screen system in promoting healthier habits and mitigating the adverse effects of prolonged screen time. The significant improvements in key health metrics and high user satisfaction ratings validate the system's potential to enhance user well-being. The AI-powered virtual assistant delivered personalised recommendations and fostered user engagement. Its ability to understand natural language queries and provide contextually relevant responses contributed to a positive user experience. Integrating multiple sensors allowed for a comprehensive assessment of user health and well-being. Real-time monitoring and analysis enabled timely interventions and proactive recommendations, promoting a more mindful approach to screen time.

4. Conclusions

The proposed smart screen system demonstrates the potential of integrating AI, IoT, and NLP technologies to promote healthier screen-time practices for long-term users. The system provides personalised interventions that encourage breaks, posture adjustments, and relaxation techniques by capturing user behaviour and monitoring key health metrics through sensors. The comprehensive data analytics engine, powered by ML and DL algorithms, offers tailored recommendations that improve user well-being and productivity. Integrating a virtual assistant enhances user interaction by delivering context-aware and empathetic guidance, thus creating a supportive digital workspace.

The results from our study indicate that the system effectively reduces stress levels, improves posture, and mitigates eye strain, as evidenced by improvements in health metrics and user satisfaction scores. By focusing on real-time monitoring and adaptive feedback, this intelligent system fosters healthier work habits, which can positively impact users' physical and mental health.

The study also acknowledges the ethical considerations of data privacy by implementing local data storage and user-centric data controls, ensuring that the system respects user autonomy and confidentiality. Future enhancements could explore expanding the system's capabilities with more advanced emotional detection and adaptive learning algorithms. The proposed smart screen system provides a promising solution for mitigating prolonged screen exposure's adverse effects, enhancing users' health and productivity in increasingly digital work environments.

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