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AI-Based Employee Healthcare and Well-Being Monitoring System with Personalized Break Recommendations

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Abstract- Sitting for long periods without moving at computer workstations is now a common part of office jobs, and it is closely linked to higher stress, tiredness, muscle and bone problems, and increased risks for heart and metabolic health over time. Traditional workplace wellness programs often respond only after problems arise, are the same for everyone, and don't consider how each employee actually works day to day, which makes them less effective. This paper introduces an AI-powered system that monitors employees' health and well-being by tracking how they use their work systems, like how long they stay active, when they take breaks, and how they interact with tools. It also includes optional data from wearable devices and information employees share about how they feel, to help identify signs of tiredness and stress. The system uses these signs to create custom pop-up messages on the employee's screen. These messages remind them to do easy health activities, like standing and stretching after sitting for a certain amount of time, or drinking water at set times for staying hydrated. A system that combines simple rules with machine learning adjusts when and how long breaks are given based on each worker's usual habits, instead of using the same schedule for everyone. A feedback loop lets the system learn from suggestions that are accepted, skipped, or rejected, helping it decrease alert fatigue over time and make the alerts more relevant. The early check of the design shows that this system can help cut down on long periods of sitting, promote better drinking habits, and make people feel more positive, all without affecting how much work they can get done. The paper also talks about the system design, the method used in the algorithm, how it is better than current solutions, and what could be done next, like keeping data private while processing it on the device and making better use of wearable devices.

Keywords— Employee Well-being, Artificial Intelligence, Health Monitoring System, Sedentary Behaviour, Personalized Recommendation, Machine Learning, Workplace Ergonomics, Pop-up Notification System, Hydration Reminder, Stress Detection, Fatigue Detection, Smart Workplace, Human-Computer Interaction, Behavioural Analytics, Wearable Sensors, Occupational Health, Break Scheduling, Digital Wellness, Predictive Health Analytics, Employee Productivity.

I. INTRODUCTION

The modern workplace is starting to depend more on long, nonstop periods of sitting at a desk and working on computers. This setup helps boost productivity in the short run, but it is often connected to harmful effects over time, like muscle and joint pain, tired eyes, not drinking enough water, higher stress, and feeling less healthy overall. Many workers stay in their seats for a long time without taking proper breaks, usually because they don't realize how long they've been working straight or because the workplace doesn't encourage them to take a pause. This habit can lead to burnout, more days off, and lower work output, which affects both the employee and the company. Current company wellness programs, like regular health check-ups, general wellness emails, or set break times, are mostly the same for everyone. They don't take into account how each person actually works, and they don't change based on when someone is feeling tired or stressed. This shows that there's a clear need for a smarter system that can quietly watch how employees work and gently suggest healthy habits at the best times. This paper introduces an AI-based system for monitoring employee health and well-being. The main idea is straightforward and easy to use. The system tracks how long an employee has been working continuously on their computer or workstation. At specific and personalized times, it shows a pop-up message reminding the employee to stand up, stretch, or take a short walk. At another set of times, it reminds them to drink water. These small prompts are backed by an AI system that learns how each employee usually works. This helps make sure reminders come at the right time, not when someone is deeply focused. The goal is to cut down on sitting too long and the health risks from not drinking enough water, while still letting employees work on their own and not messing up their productive tasks. The rest of this paper is structured like this: Section 2 looks at existing work on technology used for workplace wellness and systems that track activity; Section 3 explains the system's design and its main benefits; Section 4 describes the steps taken to create and test the system; Section 5 talks about the key findings and what can be expected from the system; Section 6 covers possible future steps for improvement; and Section 7 wraps up the paper.

II. RELATED WORK

Some previous studies are connected to the system we're talking about. These studies cover topics like making work environments more comfortable, devices that track how people move around, and computer programs that remind people to take breaks. Studies on ergonomics and workplace health show that staying in the same position for too long and not moving much can lead to body aches and other injuries. It can also make people feel more stressed and less focused during the day. This research supports the idea of taking short breaks often, but it doesn’t give a specific way to remind people to take those breaks in a real office setting using technology. Consumer wearable devices, like fitness bands and smartwatches, already offer simple "move" or "stand" reminders that happen at fixed times each hour and track heart rate. However, these reminders aren't tailored to how an individual actually works on their computer. They also don't connect with company well-being dashboards, and usually, the employee needs to have and wear a separate device all the time. Software-based break-reminder apps, like simple desktop timers that tell you to take a break after a set amount of time, help with the problem of sitting too long. But they only help a little because they use the same fixed timer for everyone, no matter what they're doing or how they work. They don’t take into account how different people work, how hard a task is, or how stressed someone feels. They also don’t learn from what users do, like if someone keeps ignoring the reminders. Recent studies in emotional computing and workplace analysis have looked into using things like how people type, move their mouse, and interact with computers as cheap and unobtrusive ways to measure how engaged, tired, or stressed someone is. These methods could help understand someone's mental and physical state without needing extra equipment. However, there aren't many full systems that put all these signals together with a customized tool that suggests breaks to improve overall well-being in organizations. The system uses these ideas by bringing together computer usage tracking, optional wearable data, self-reported updates, and a learning-based recommendation system into one personalized tool that helps improve well-being at work.

III. PROPOSED SYSTEM

The proposed system is an AI-based Employee Healthcare and Well-Being Monitoring platform that runs quietly in the background on an employee's workstation and delivers personalized, well-timed wellness reminders. Conceptually, the system is organized into five functional layers that work together. The data collection layer passively records continuous active working time on the employee's computer along with idle-time gaps, and is optionally supplemented by wearable data such as heart rate and activity level, as well as periodic, voluntary self-reported mood or stress check-ins on a simple 1–5 scale, with all collection kept minimal, transparent, and consent-based. The processing and inference layer analyses these signals using a combination of threshold-based rules and lightweight machine-learning models to detect sustained continuous-sitting periods and to flag rising fatigue or stress indicators relative to the employee's own historical baseline rather than a fixed population-wide threshold. The personalized recommendation engine then decides when and what type of break to suggest: a stand-and-stretch reminder triggered after a defined, personalized continuous-sitting interval, and a separate hydration reminder triggered at a regular interval, with the ability to escalate to a longer break when combined signals — such as extended activity together with a low self-reported mood score — indicate elevated fatigue or stress. These recommendations are delivered through the notification and user-interface layer as short, non-intrusive pop-ups timed to avoid interrupting critical tasks, alongside a personal dashboard showing the employee's own trends over time, while any organizational-level dashboard only receives aggregated, anonymized data. Finally, the feedback loop records whether each recommendation is accepted, snoozed, or dismissed and uses this response to adjust future timing and frequency for that individual, reducing unnecessary interruptions for employees who already take regular breaks while increasing reminders for those who consistently ignore early signs of prolonged sitting or dehydration.

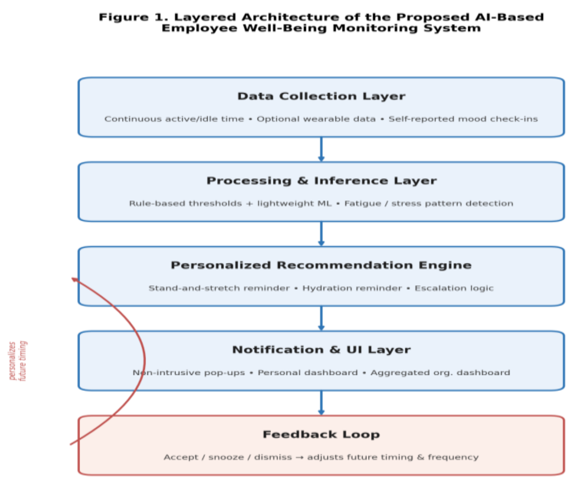

Figure 1. Layered architecture of the proposed AI-based employee well-being monitoring system, showing the flow from data collection through to the feedback loop.

Unlike existing fixed-timer break applications, the proposed system treats these intervals as personalized parameters rather than fixed constants, tuning itself to each employee's working rhythm while maintaining a strong privacy boundary in which raw behavioural data stays associated with the individual and only aggregated, anonymized trends are ever shared at the organizational level.

This design has more benefits compared to other ways of improving workplace wellness. Its personalization makes sure that break times fit each employee's individual work pace instead of everyone following the same set schedule. The simple core reminders, like stand-and-stretch and drink-water pop-ups, provide real value without needing any special equipment. The feedback loop helps keep the design unobtrusive by figuring out when reminders are accepted versus ignored, which then helps promote regular movement and drinking water, and lowers the chances of muscle and joint problems, eye tiredness, and fatigue from not drinking enough over time. The design also focuses on privacy, because each person's information stays with them, and only grouped, nameless patterns are shared at the company level, which helps create trust and makes people more willing to use the system. Because the system uses a mix of rules and machine learning that doesn't need a lot of computing power, it can work well even with a big team. The trends it gathers, which are combined and made anonymous, give companies useful information about workplace health. For example, it can help find out which departments often don't take their breaks as needed.

IV. METHODOLOGY

The methodology followed to design, build, and evaluate the proposed system consists of five sequential stages. The first stage, requirement analysis, involved identifying the core well-being problems faced by desk-based employees — prolonged sitting and insufficient hydration — and translating them into measurable system requirements: detecting continuous sitting/working time per employee and prompting hydration at a regular, configurable interval, alongside secondary requirements such as minimal intrusiveness, privacy protection, and adaptability to individual routines drawn from related workplace-wellness and break-reminder literature. The second stage, data acquisition and simulation, relied on two complementary sources for design and testing, since live organization-wide deployment requires ethical approval and employee consent: system-level activity logs (active/idle time, application-switch frequency) captured directly from the employee's workstation with consent, and synthetic activity datasets simulating a range of working patterns — short bursts, long uninterrupted sessions, irregular schedules — for offline testing of the recommendation logic before live deployment. The third stage, rule and model design, adopted a hybrid approach in which baseline stand-and-stretch and hydration reminders were implemented as configurable threshold rules (for example, a stand reminder after 60 minutes of continuous activity and a hydration reminder every 45–60 minutes), on top of which a lightweight machine-learning layer — using rolling statistical baselines and simple classifiers such as decision trees or Isolation Forest for anomaly detection — personalizes these thresholds per employee based on their own historical activity and their pattern of accepting, snoozing, or dismissing past reminders. The fourth stage, prototype implementation, involved building a lightweight background application/service on the employee's workstation paired with a simple notification interface for pop-ups and a personal dashboard for viewing trends, with backend logic structured so that new signals, such as wearable heart-rate data, could be added incrementally without redesigning the core system. The fifth and final stage, evaluation, compares the proposed personalized system against a fixed-interval baseline reminder system using metrics such as average continuous sitting time before a break, hydration-reminder acceptance rate, and reminder dismissal rate, together with self-reported well-being scores collected before and after adoption where live deployment is available, in order to test the central hypothesis that adaptive, individualized reminder timing produces better adherence and lower alert fatigue than a static, one-size-fits-all schedule.

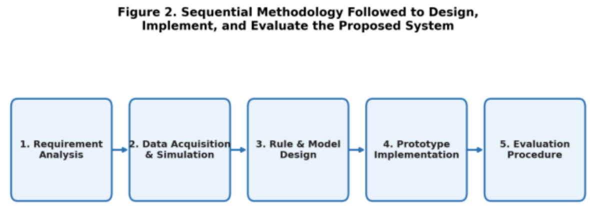

Figure 2. Sequential methodology followed to design, implement, and evaluate the proposed system.

V. MAIN RESULTS

The proposed AI-based Employee Healthcare and Well-Being Monitoring System is expected to produce several positive outcomes in workplace health management. The system can reduce prolonged periods of sitting by providing timely and personalized reminders for employees to stand, stretch, walk, or take short recovery breaks. It is also expected to improve hydration habits through regular and customized water reminders. Since the system learns from individual working patterns, it can recommend suitable break times and durations without unnecessarily interrupting important work activities. Another expected result is improved employee engagement with wellness recommendations. By analyzing whether notifications are accepted, skipped, or dismissed, the system can gradually reduce unnecessary alerts and minimize notification fatigue. Personalized recommendations are expected to achieve higher adherence rates than conventional fixed-interval reminders. The system can also identify patterns associated with prolonged inactivity, fatigue, or increased workload and provide appropriate wellness suggestions at suitable times. The proposed system is further expected to improve self-reported well-being by encouraging regular movement, hydration, and short recovery periods during working hours. Employees may experience reduced physical and mental fatigue, improved comfort, and better awareness of healthy workplace habits. At the same time, productivity can be monitored through task completion time, work output, or activity levels to ensure that recommended breaks do not significantly affect performance. The expected outcome is that short, well-timed breaks can support employee health while maintaining stable productivity. In addition, the system can provide useful analytical information about general workplace activity patterns, break adherence, and recommendation effectiveness. The adaptive learning mechanism allows the system to continuously improve its recommendations based on employee feedback and behavioral patterns. Privacy-preserving techniques can also be incorporated to protect sensitive employee information and limit unnecessary health-data collection. Overall, the expected results indicate that an AI-driven personalized approach can provide more effective, flexible, and employee-centered wellness support than traditional one-size-fits-all break reminder systems.

Future Work

In the future, there are several possible ways to improve or expand the proposed system. Processing behavior data directly on the employee's device or at the edge of the network helps protect privacy. This way, the original activity data never leaves the employee's machine, which reduces the need for central servers and makes employees feel more confident that their work habits aren't being watched from outside. By better connecting with wearable devices to track heart rate, sleep, and steps, we can more accurately figure out stress and tiredness. This is done by looking at both body signals and how people use their computers, instead of just relying on activity levels. Including posture-detection with clear permission from users can help give better stand-and-stretch advice by spotting bad sitting habits as well as long periods of sitting. Also, personalized break suggestions like guided stretches, breathing exercises, or short mindfulness activities, based on what kind of tiredness or stress someone is feeling, can make breaks more helpful instead of giving the same basic advice to everyone. The recommendation system could be improved by using more advanced models that work with time-based data, like LSTM models, to better understand slow, ongoing tiredness patterns that happen over a whole day, instead of just looking at quick, short-term changes. Using notifications in multiple languages and different voices might help make reminders easier to understand and feel more natural for a wide range of employees. Looking beyond each individual worker, longer studies that cover the whole organization and take place over many months can help confirm how effective the system is in real-life situations.These studies would show how the system affects things like missing work, using sick leave, being productive, and overall health in the long run, which goes beyond what short-term pilot tests can show. Finally, federated learning methods could be used to let the recommendation system get better across many employees and companies without gathering sensitive personal information in one place.Also, connecting with wider enterprise HR and workplace health systems could let well-being data influence company policies in a way that keeps privacy and uses combined information.

VI. CONCLUSION

This paper describes the creation of an AI-powered system that monitors employee health and well-being. It provides customized, on-time pop-up messages that remind workers to stand up, stretch, and drink water during extended work periods. The system was inspired by a simple but important truth about work: people who sit at their computers for long periods without breaks are more likely to feel stressed, develop body aches, get dehydrated, and feel tired. However, most current wellness programs are not tailored to how each person actually works, and they don't change or grow with the needs of the workers. The system uses light computer activity tracking, optional wearable devices, and self-reported information along with a mix of rule-based and machine learning to suggest reminders. It adjusts to each person's unique work habits instead of using the same set reminders at fixed times. The system keeps getting better at timing and how often to send reminders by learning from how each employee responds. The proposed method is easy to set up, barely noticeable, and focused on privacy. Each person’s personal behavior data stays with them, and only general, nameless trends are shared at the company level. This approach has the chance to cut down on sitting time, help people drink more water, and boost their overall health and happiness, all while keeping work performance the same or better. When you look at the design, approach, and results mentioned in this paper, it becomes clear that even simple, well-timed reminders — based on a clear understanding of how each employee works — can make a real difference in workplace health. These nudges are easy to put in place and don't cost much, which means the system is both useful and something companies can easily use along with their current wellness efforts. Future work will aim to improve privacy by doing more processing directly on the device, enhance integration with wearables and posture tracking, improve the recommendation system using better time-based models, and test the system's real-world effects through bigger, long-term studies within organizations. The goal is to develop a fully mature and flexible well-being platform that any size of organization can confidently use.

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