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PULSE - PERSONALIZED UNDERSTANDING, LEARNING AND WORKING STRESS EVALUATION

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Abstract

Work-related stress has become a pervasive challenge with significant social and economic implications. This paper presents PULSE, a holistic digital system designed for Personalized Understanding, Learning, and Working Stress Evaluation in modern workplaces. The proposed system integrates non-invasive wearable sensors, IoT devices, and affective computing techniques to continuously monitor physiological, behavioral, and environmental indicators of stress. Advanced machine learning algorithms analyze these multimodal data in real time to detect stress levels, while a personalized e-learning platform delivers adaptive interventions (such as mindfulness exercises and cognitive-behavioral strategies) to help individuals manage stress proactively. A gamified mobile application interfaces with users, providing feedback and motivation to engage in stress-reduction activities. The paper also outlines a pilot study plan in a real workplace environment to evaluate the system's effectiveness. By combining accurate stress detection with tailored just-in-time support, PULSE aims to promote mental well-being and enhance productivity in the workplace.

***Keywords*:**

Affective Computing, E-Learning, Occupational Health, Work-Related Stress, Wearable Sensors

1. Introductions

Work-related stress remains a pervasive and costly challenge worldwide, exerting profound effects on both individual well-being and organizational productivity. More than half of workers report experiencing stress as a common problem, and approximately 60% of lost workdays are attributed to psychosocial risks [1]. Chronic exposure to occupational stressors contributes not only to mental health problems such as anxiety, depression, and burnout, but also to physical ailments including fatigue, musculoskeletal disorders, and cardiovascular disease [2]. In Greece, the situation is particularly concerning: 64% of employees report intense workplace stress, 48% acknowledge being unable to manage it effectively, and only 23% feel adequately supported by their employers [3]. These statistics underscore the urgent need for proactive and evidence-based approaches to stress management within organizational contexts.

Traditional stress-management practices, including self-reports, workshops, and periodic seminars, remain limited by subjectivity, recall bias, and delayed feedback. They often fail to provide timely, personalized insights into employees' emotional states, resulting in interventions that are reactive rather than preventive. In contrast, affective computing offers a transformative framework for continuous and objective assessment of psychological well-being. By integrating multimodal data streams, affective computing systems can automatically detect stress through a combination of psychological, physiological, and behavioral indicators. Psychological measures may include validated questionnaires and ecological self-reports, while physiological indicators encompass heart rate variability, skin conductance, respiration rate, and peripheral skin temperature. Behavioral indicators, such as facial expressions, body posture, speech tone, and digital interaction patterns, provide additional context for understanding emotional dynamics in real time.

The incorporation of ambient Internet of Things (IoT) sensors further enhances the potential of these systems. By monitoring environmental parameters such as temperature, noise levels, lighting, and air quality, smart offices can contextualize affective data and create adaptive, minimally intrusive monitoring environments [6], [8]. This integration supports a holistic view of workplace well-being, allowing organizations to identify stressors and implement responsive interventions before they escalate into health or performance issues.

Equally important to detection is the ability to deliver effective and timely support. Digital interventions—particularly those grounded in cognitive-behavioural therapy (CBT)—offer scalable, flexible, and stigma-free solutions for stress management [7]. Through online platforms or mobile applications, employees can access personalized coping strategies, mindfulness exercises, and psychoeducational content at their convenience. To maximize engagement and adherence, these digital programs increasingly incorporate elements of gamification, such as progress tracking, achievement badges, and social or team-based challenges, which foster motivation and sustained participation [9].

The convergence of affective computing, IoT-enabled environments, and digital therapeutics signals a paradigm shift in occupational health management. Together, these technologies enable a proactive, data-informed approach to identifying and mitigating stress in real time. Future developments should prioritize ethical considerations, including data privacy, algorithmic transparency, and user consent, to ensure responsible adoption and build trust among employees and organizations alike. Research question: How can Machine Learning, IoT, and Affective Computing be combined to enhance real-time stress detection accuracy and seamlessly integrate with personalized interventions that promote employee well-being and productivity?

2. The Pulse System

The PULSE framework constitutes a comprehensive, two-pillar solution designed to address workplace stress through adaptive management and continuous monitoring. The first pillar focuses on adaptive stress management and intervention, providing timely, personalized support to employees. The second pillar centers on continuous stress monitoring and detection, utilizing multimodal sensing technologies to capture physiological, behavioral, and environmental indicators of stress in real time. Together, these components form an integrated system capable of both identifying stress patterns and delivering tailored, evidence-based interventions to improve employee well-being.

Within the monitoring and detection domain, the system leverages wearable technologies such as smartwatches and wristbands to record physiological parameters, including heart rate, heart-rate variability, electrodermal activity, skin temperature, and motion. These continuous data streams provide objective insight into the autonomic nervous system's response to stress. Complementary behavioral indicators are derived from multiple modalities, such as voice characteristics (including tone and pitch), typing patterns, and, where user consent is obtained, webcam-based assessments of facial expressions and posture. All behavioral data collection adheres to strict privacy and ethical safeguards, ensuring transparency and user trust. In parallel, ambient sensors within the workplace environment monitor contextual parameters such as temperature, humidity, noise levels (in decibels), carbon dioxide concentration, volatile organic compounds, and light intensity. These data contribute to a holistic understanding of how environmental factors interact with individual stress responses.

The system's workflow is designed as a continuous pipeline of data acquisition, preprocessing, analysis, and adaptation. Initially, data from various sources are acquired and synchronized via Bluetooth or Wi-Fi connections. Preprocessing techniques are applied to remove outliers, interpolate missing values, align timestamps, and normalize data using methods such as min–max scaling, z-score normalization, and personal baseline calibration. Subsequently, relevant features are extracted from multiple domains. Time-domain features include statistical measures such as mean, standard deviation, and root mean square values, while frequency-domain analyses employ Fast Fourier Transform and wavelet decomposition to examine heart-rate variability bands. Behavioral features encompass speech rate and keystroke dynamics, and environmental features capture metrics such as noise intensity and thermal comfort indices.

Feature selection techniques—including correlation pruning, principal component analysis, recursive feature elimination, and model-based importance ranking—are employed to identify the most informative predictors for stress classification. The refined feature set is then used to train machine-learning models such as ensemble methods (XGBoost, Random Forest), support vector machines, and neural networks. To enhance accuracy and relevance, the models are personalized by fine-tuning general models on individual data and clustering users with similar stress-response patterns through unsupervised learning methods such as k-means. The system incorporates continuous learning by allowing users to provide self-reported annotations, for example, noting periods of stress before meetings or deadlines. These annotations refine personal thresholds over time, reducing false positives and improving the precision of stress detection.

When elevated stress levels are identified, PULSE activates its adaptive management and intervention component. The mobile application and e-learning platform deliver personalized, context-aware support modules covering mindfulness, breathing exercises, cognitive-behavioral reframing, micro-stretch breaks, and time-management strategies. Content delivery is dynamically adjusted based on real-time stress levels and inferred contextual stressors—for instance, prompting relaxation techniques before a scheduled meeting or suggesting brief recovery breaks during high workload periods. The system learns which coping mechanisms are most effective for each individual, refining future recommendations based on engagement patterns and reported outcomes.

To sustain participation and promote behavioral change, the platform incorporates gamification elements that transform stress management into an engaging experience. Users earn points, badges, and levels by completing exercises and maintaining daily streaks, while habit trackers and reminders support consistency. Team-based and individual challenges, such as completing multiple stress-relief exercises within a week, foster motivation and social connectedness. An interactive scenario-based game further enriches engagement by allowing users to navigate simulated workplace situations through personalized avatars, generating "coping-style" profiles and tailored feedback. Comprehensive progress dashboards visualize individual stress trends, highlighting reductions in peak stress episodes and improvements in overall resilience. All user interactions, performance metrics, and feedback are continuously integrated into the learning loop, enabling the system to refine both predictive accuracy and intervention effectiveness over time.

The PULSE system architecture is composed of three interconnected layers. The sensor layer encompasses personal wearable devices and ambient IoT hubs responsible for continuous data collection. The edge and server layer manages secure data ingestion, preprocessing, machine-learning inference, and encrypted database storage. Finally, the user interface layer delivers the processed insights through intuitive applications. The mobile application provides stress feedback, real-time notifications, and access to gamified stress management activities, while a web-based dashboard offers optional desktop access to long-term trends and analytics. The integrated e-learning platform operates as an open-source, SCORM-compliant learning management system, featuring modules for courses, forums, and quizzes with customizable organizational branding.

End-to-end encryption ensures that all data, both in transit and at rest, remain secure. Access controls, pseudonymization, and anonymization protocols are strictly enforced to protect user identity and comply with data protection standards. By integrating physiological, behavioral, environmental, and contextual intelligence within an ethically responsible framework, PULSE represents a scalable, adaptive, and privacy-conscious solution for proactive workplace stress management.

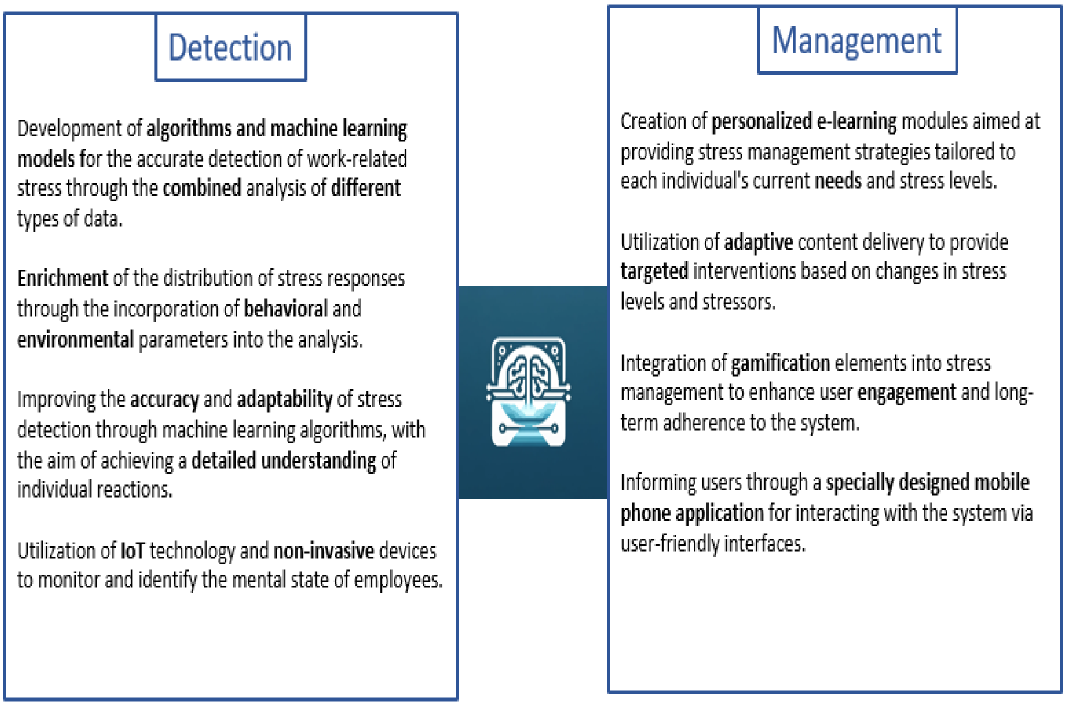

Fig. 1: *Summary of the Key Objectives of the Pulse Project*

3. Stress Detection Model Development

The development of the stress detection model within the PULSE framework follows a robust, end-to-end pipeline designed to transform raw multimodal signals into accurate and interpretable stress scores. This process encompasses systematic data preprocessing, comprehensive feature extraction, and advanced machine learning techniques augmented with personalization strategies to ensure both precision and adaptability across individuals.

The preprocessing stage serves as the foundation for reliable model performance. Incoming physiological and behavioral signals are first cleaned to detect and remove anomalous readings, such as heart rates exceeding 200 beats per minute, as well as motion-induced artifacts that can distort measurements. Short-term signal dropouts are interpolated where appropriate, while longer gaps are marked as missing to prevent the introduction of artificial trends. Normalization procedures are applied globally—using methods such as min–max scaling or z-score standardization—and locally, through personal baseline adjustments that account for inter-individual variability in physiological reactivity. To ensure temporal coherence, all multimodal data streams, including physiological, behavioral, and environmental inputs, are synchronized to a unified timeline. When computational efficiency or redundancy becomes a concern, dimensionality reduction techniques such as principal component analysis (PCA) are optionally employed to retain the most informative components.

Feature extraction translates the preprocessed signals into quantitative descriptors of stress-related patterns. Time-domain features capture statistical properties such as mean, variance, root mean square, and derivative-based dynamics that reflect moment-to-moment fluctuations in physiological activation. Frequency-domain analyses examine the spectral characteristics of heart-rate variability, including low- and high-frequency power components and spectral entropy, which provide insights into autonomic balance and arousal states. Behavioral metrics are derived from variations in speech pitch and keystroke latency, indicators of cognitive load and emotional tension. Environmental indices, such as average noise levels and composite thermal comfort scores, contextualize physiological and behavioral responses within the surrounding workspace. To optimize model efficiency, redundant or weakly informative features are removed using correlation thresholding, recursive feature elimination, and feature-importance analysis derived from tree-based ensemble models.

Machine learning constitutes the core analytical layer of the pipeline, enabling the system to infer stress states from the extracted features. A range of algorithms is employed, including ensemble methods such as XGBoost and Random Forest, as well as support vector machines and feedforward neural networks. The models are initially trained on labeled datasets derived from controlled stress-induction experiments, such as cognitive load tasks and simulated public speaking scenarios, which provide reliable ground truth labels for physiological and behavioral responses. These models are subsequently refined using real-world pilot data collected during natural workplace conditions to enhance ecological validity. Performance is evaluated through rigorous cross-validation and statistical metrics, including accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC). Confusion matrix analyses further clarify model strengths and weaknesses across different stress levels.

To enhance personalization and generalizability, transfer-learning techniques are employed to adapt pre-trained general models to individual users using small sets of personalized data. Additionally, user clustering based on response patterns enables the creation of semi-personalized models that balance individual specificity with population-level robustness. Statistical validation methods, including t-tests and analysis of variance (ANOVA), confirm that extracted features differ significantly between stress and baseline conditions, thereby supporting the discriminative validity of the selected features and ensuring the reliability of the resulting stress detection models.

Through this integrated modeling framework, the PULSE system achieves continuous, context-aware stress detection with both population-level applicability and individual-level adaptability—an essential capability for real-world deployment in dynamic occupational environments.

Figure 2: *Interactive Learning Pathways for Reducing Stress at Work*

4. E-Learning Platform and Mobile App

The PULSE e-learning platform and mobile application function as complementary components of the overall stress management ecosystem, designed to deliver continuous, personalized, and evidence-based support to employees. Together, they form the user-facing layer of the system, translating data-driven stress insights into meaningful behavioral interventions and educational opportunities.

The e-learning platform serves as an interactive training environment that integrates theoretical knowledge, practical exercises, and community-based engagement. It includes a curated library of educational videos featuring expert-led guidance and techniques for managing stress, drawing on established principles from psychology and occupational health. In parallel, a collection of lectures and presentations provides users with research-informed content explaining the mechanisms, consequences, and mitigation strategies for workplace stress. To bridge theory and practice, the platform incorporates self-help tools and exercises, including mindfulness training, breathing techniques, progressive muscle relaxation, and cognitive-behavioral reframing activities aimed at enhancing resilience and emotional regulation. A discussion forum fosters social interaction and peer support, enabling users to share experiences, exchange coping strategies, and participate in collaborative well-being initiatives. This integrated structure not only supports self-paced learning but also promotes a sense of belonging and collective motivation among participants.

The mobile application complements the e-learning platform by providing real-time stress feedback and adaptive intervention delivery. Using data derived from the continuous monitoring framework, the app identifies periods of elevated stress and triggers context-aware recommendations such as short breathing exercises, brief mindfulness sessions, or ergonomic micro-breaks. Dynamic scheduling algorithms adjust the frequency and type of interventions based on temporal patterns (e.g., pre-meeting reminders or end-of-day relaxation prompts) and individual response histories. The app further integrates gamification elements to sustain engagement—users earn points, badges, and levels for completing activities, maintaining daily streaks, and participating in team-based challenges. Interactive visualizations and progress dashboards allow users to track their physiological and behavioral trends, observe reductions in stress episodes, and reflect on their long-term improvement.

Both the e-learning platform and mobile app adhere to high standards of data privacy, personalization, and accessibility. User information is encrypted end-to-end, and all health-related data are stored pseudonymously to protect identity. Adaptive interfaces ensure usability across diverse devices and user preferences, while accessibility features accommodate individuals with varying levels of digital literacy. Collectively, these digital components transform stress management from a reactive process into a proactive, interactive, and user-centered experience, aligning with modern trends in digital health and occupational well-being.

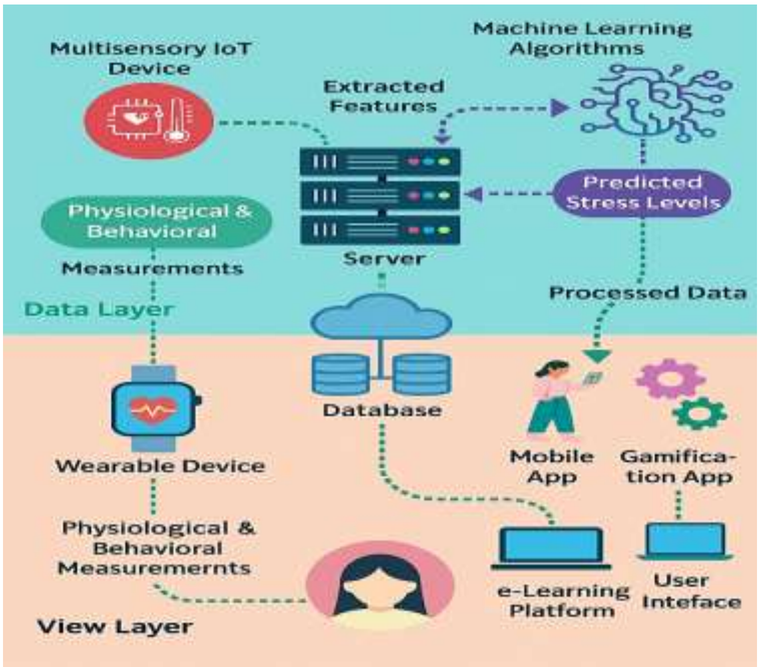

Figure 3: *Architecture of the Pulse System*

5. Pilot Study Plan

A pilot study is planned to evaluate the feasibility, usability, and preliminary effectiveness of the PULSE system within a real-world occupational setting. The study will be conducted at the ART Palace elderly-care facility in Maroussi, Greece, involving two distinct staff groups: office personnel and frontline caregivers. Approximately twenty-five volunteers will be recruited, comprising employees without major cardiovascular conditions and who own Android smartphones compatible with the PULSE mobile application.

The pilot will span eight months, including a two-month setup and calibration phase followed by six months of full operational deployment. During the onboarding process, participants will attend hands-on orientation sessions led by an on-site psychologist, ensuring proper use of wearable devices, mobile applications, and the e-learning platform. Instructional materials, including user manuals and frequently asked questions (FAQs), will be provided to facilitate independent troubleshooting and consistent engagement throughout the study period.

Data collection will encompass multiple quantitative and qualitative sources. Physiological and behavioural sensor streams, along with computed stress scores, will be continuously recorded. The mobile application will log user engagement metrics, such as module completion rates, points earned through gamified activities, and responses to app notifications. Periodic self-reports will be administered using the Perceived Stress Scale (PSS) at baseline, midpoint, and post-intervention to assess subjective stress changes over time. In addition, qualitative feedback will be gathered through semi-structured interviews and focus group discussions to capture participants' perceptions, challenges, and suggestions for improvement.

The study will evaluate system performance across several key metrics. Detection accuracy will be assessed by comparing model-generated stress predictions against self-reported stress levels and identifiable stress-inducing events in the workplace. Engagement will be analysed based on sustained system usage, frequency of app interactions, and completion statistics for digital learning modules. Effectiveness will be measured through reductions in perceived stress levels, as well as secondary indicators such as changes in sick-leave frequency. Usability will be evaluated using the System Usability Scale (SUS) and corroborated by qualitative user satisfaction feedback. Finally, feasibility will be examined through indicators such as sensor reliability, device battery life, data transmission stability, and user-reported burden associated with system use.

Insights derived from this pilot will inform iterative refinements to both the hardware and software components of PULSE. Specifically, findings will guide model retraining to enhance detection accuracy, adjustments to data processing algorithms, and revisions to intervention content and delivery strategies. The results will thus play a pivotal role in optimizing the system's scalability and readiness for larger-scale deployment across diverse occupational settings.

6. Expected Results and Impact

The implementation and evaluation of the PULSE system are anticipated to generate significant financial, social, and scientific–technological impacts, contributing to both organizational sustainability and employee well-being.

From a financial perspective, the system is expected to reduce costs associated with absenteeism and presenteeism by enhancing workforce productivity and minimizing the need for temporary replacements. The proactive detection and management of stress are also projected to yield considerable healthcare savings, as fewer employees are likely to experience stress-related disorders such as chronic fatigue, anxiety, and musculoskeletal complaints. Furthermore, evidence from previous studies suggests that investments in workplace mental-health interventions deliver a high return on investment (ROI), with each euro invested potentially yielding €5–13 in returns within a year through reduced healthcare expenditures and productivity losses [13], [14].

The social impact of the PULSE initiative is equally substantial. By promoting stress awareness and providing accessible digital tools for self-regulation, the system is expected to enhance overall employee well-being, reduce anxiety levels, and improve job satisfaction. The structured interventions and community-based features of the platform—such as discussion forums and shared challenges—are designed to foster positive team dynamics and strengthen interpersonal support within the workplace. Importantly, the initiative contributes to stigma reduction by normalizing conversations around stress and mental health, thereby encouraging early help-seeking behaviors. Over time, this approach is expected to support a broader organizational culture shift, embedding psychological safety, open dialogue, and holistic well-being into the core of workplace practices.

From a scientific and technological standpoint, the project is positioned to advance the state of knowledge in multiple domains. The continuous collection of multimodal physiological, behavioural, and environmental data in authentic workplace settings offers a unique opportunity to identify novel stress biomarkers and validate their ecological relevance. The project will also contribute to methodological innovation in machine learning personalization, developing hybrid models that balance generalization with user-specific adaptation through clustering and transfer-learning strategies. Additionally, PULSE provides empirical evidence on gamification in e-health, elucidating which design elements most effectively sustain long-term engagement and behavior change. Finally, by capturing longitudinal data on stress and recovery cycles within real work contexts, the study will deepen understanding in occupational psychology, offering valuable insights into the temporal dynamics of well-being and performance.

Collectively, these anticipated outcomes position PULSE as a transformative contribution to both workplace health management and digital health innovation, demonstrating that technology-enabled, human-centered solutions can simultaneously enhance economic efficiency, social resilience, and scientific progress.

7. Exploitation Strategy

The exploitation strategy of the PULSE project is designed to ensure that the outcomes of research and development are translated into tangible, long-term benefits for academia, industry, and society. Each partner organization will contribute to and benefit from the project's results through targeted pathways aligned with their institutional missions and expertise, ensuring both sustainability and fair benefit sharing.

Harokopio University will lead the academic dissemination of project results through peer-reviewed publications, conference presentations, and the pursuit of new research grants that build on the project's findings. The knowledge generated from PULSE will also be integrated into university curricula, particularly within courses related to affective computing, occupational health, and digital psychology. In addition, the project will serve as a foundation for doctoral and postgraduate research, fostering capacity building and continued innovation in stress detection and digital health technologies.

Computer Solutions S.A. will focus on the commercial exploitation of PULSE as a scalable offering within the domains of corporate wellness, occupational health, and healthcare services. The company will explore pathways for market deployment, emphasizing interoperability, ease of integration, and data security. Intellectual property (IP) arising from the technological components—such as the stress detection algorithms, system architecture, and e-learning modules—will be protected through appropriate IP management strategies, enabling sustainable commercialization and product evolution.

ART Place, as the primary end-user partner, will leverage the system to improve staff well-being and enhance the quality of care services delivered within its facility. The successful deployment and evaluation of PULSE in this environment will serve as a demonstration case, allowing ART Palace to extend its role as a consultant or training partner to other elderly-care institutions seeking to implement evidence-based well-being programs.

Toolbox Consulting will capitalize on its expertise in GDPR compliance and digital transformation to support the broader adoption of PULSE within corporate and institutional contexts. The company will develop strategic deployment roadmaps, ensuring that future implementations adhere to regulatory standards and data protection principles while aligning with organizations' digital wellness objectives.

A transparent intellectual property and licensing framework will govern ownership, access rights, and revenue sharing among partners. This framework will ensure equitable benefit distribution, promote open collaboration where appropriate, and support the long-term maintenance, scalability, and sustainability of the PULSE solution beyond the project's duration.

8. Risk Management & Ethical Considerations

A. Key Risks & Mitigations

Risk	Mitigation Strategy
Low user engagement	Implement continuous engagement strategies including regular coaching sessions, personalized feedback, and motivational support from the onsite psychologist. Gamification elements and recognition incentives will further encourage sustained participation and adherence.
Technical integration issues	Employ an agile development framework with built-in contingency buffers. Maintain modular architecture and multiple sensor/algorithmic alternatives to ensure system robustness and interoperability across devices and platforms.
Consortium coordination breakdown	Establish a structured governance framework led by a monthly Steering Committee to ensure transparent communication and progress alignment. Define clear partner roles and responsibilities, supported by collaborative project management and documentation tools.
Budget overruns	Conduct quarterly financial reviews to monitor expenditure and forecast deviations early. Apply adaptive feature prioritization and cost–benefit analysis to maintain project scope within financial constraints without compromising core deliverables.

B. Key Risks & Mitigations

The ethical and data protection framework of the PULSE project is designed to uphold the highest standards of participant welfare, privacy, and transparency. This framework identifies and mitigates key risks related to data handling, user rights, and ethical compliance, ensuring that the research adheres to both legal obligations and ethical best practices.

A central element is the principle of informed consent. All participants will receive a clear and comprehensive explanation of the project's objectives, the nature of the data collected, and the specific purposes of their use. Participation will be entirely voluntary, with the right to withdraw at any time without consequences. Consent materials will be presented in accessible language to ensure comprehension and informed decision-making across diverse participant groups.

To preserve confidentiality, all personal data will be protected through pseudonymization and encryption, both during storage and transmission. Unique participant identifiers will replace direct personal identifiers, and secure communication protocols will prevent unauthorized access or potential data breaches. In alignment with data minimization principles, only essential physiological, behavioral, and environmental indicators will be collected. The system will not store raw audio, video, or text data; instead, such inputs will be processed locally to extract anonymized features, thus maintaining privacy while retaining analytical value.

Participants will retain full control over their data, including the right to access, correct, or request deletion of their personal information in accordance with the EU General Data Protection Regulation (GDPR). Transparent procedures will be established to facilitate these actions efficiently. Furthermore, a data retention policy will define precise timelines for data storage, specifying when personal information will be deleted or irreversibly anonymized after study completion.

All study procedures are conducted in strict compliance with the Declaration of Helsinki and EU data-protection laws, ensuring participant welfare, respect for autonomy, and the highest level of data integrity. These safeguards collectively reinforce participant trust, promote responsible innovation, and position PULSE as a model for ethical digital health research and deployment within real-world occupational environments.

9. Dissemination & Communication

The dissemination and communication strategy of the PULSE project is designed to ensure broad visibility, stakeholder engagement, and knowledge transfer across academic, industrial, and public domains. By combining digital outreach, academic dissemination, and industry engagement, the strategy aims to maximize the project's scientific, technological, and societal impact while promoting awareness of digital stress management innovations.

A dedicated project website and associated social media channels will serve as the primary communication platforms, providing regular updates on project milestones, achievements, and events. These platforms will feature infographics, short-form articles, and a continuously updated blog offering evidence-based "stress management tips," thereby extending the project's relevance to both professional audiences and the general public.

Academic dissemination will be achieved through publications and presentations at leading conferences and journals, including IEEE, ACM CHI, and health informatics venues.

Open-access publishing will be prioritized wherever possible to ensure wide accessibility of research outputs and to foster collaboration within the scientific community.

Industry engagement will occur through demonstrations and webinars, targeting HR technology fairs, corporate wellness events, and digital health expos. Pilot showcase sessions will provide tangible demonstrations of the PULSE system's capabilities, allowing stakeholders to explore its real-world applications and benefits.

To enhance outreach effectiveness, a suite of multimedia communication assets will be developed. These will include an animated short film depicting "a day in the life of PULSE," visually illustrating the system's end-to-end functionality and user experience. Complementary materials such as press releases, promotional videos, and ROI-focused infographics will further communicate the project's economic and human-value proposition to decision-makers and the broader public.

Knowledge transfer and stakeholder engagement will also be supported through thematic workshops and white papers. These events and publications will share best-practice guidelines for the design, deployment, and ethical use of digital stress management interventions, targeting policymakers, occupational health professionals, and technology providers.

The effectiveness of dissemination activities will be continuously assessed through measurable indicators such as website analytics, publication and download counts, social media engagement, event attendance, and media coverage. These metrics will guide iterative improvements in communication strategy and ensure that the project maintains high visibility and impact across its entire lifecycle.

10. Conclusions

The PULSE system embodies a unified, data-driven approach to workplace stress management by seamlessly integrating unobtrusive multimodal sensing with adaptive, gamified e-learning interventions. Through this closed-loop framework, linking continuous stress detection with personalized, real-time support,PULSE moves beyond traditional reactive models toward a proactive paradigm of employee well-being. By combining physiological, behavioral, and environmental insights with evidence-based digital interventions, the system aims to reduce stress, enhance productivity, and promote sustained engagement in healthy work practices.

The forthcoming pilot study will provide critical validation of PULSE's feasibility, usability, and effectiveness in authentic occupational settings. The insights gained will inform iterative refinements in both technology and content, ensuring that future deployments are scalable, user-centered, and ethically sound.

Ultimately, PULSE aspires to redefine workplace well-being by transforming organizational environments into spaces where technology actively empowers resilience, balance, and psychological safety. In doing so, it contributes not only to healthier and more productive employees but also to a broader cultural shift—one where digital innovation and human-centered design converge to foster sustainable well-being across the modern workforce.

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