Intelligent Mental Workload Mobile Application in Personalized Digital Care Pathway for Lifestyle Chronic Disease

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Abstract. In the new healthcare paradigm, personalized digital care pathway enables the provision of tailored information and empowers patients. In healthcare, it is crucial to attend to patients' physical and emotional requirements. Stress and heavy mental workload can be detrimental to managing chronic lifestyle disorders. However, a reliable, standardized, and widely used paradigm for incorporating mental workload into the digital care pathway for providing long-term personalized care is missing from the current care pathway. Therefore, this study aims to investigate the use of mental workload tools and mobile applications in personalized digital care pathways for managing lifestyle chronic diseases. The study was focused on determining and characterizing the variables that determine mental workload; and then, investigating the ways in which these variables might function as supplementary data sources to enhance the personalization of care pathway. Based on the proposed mental workload tool, data was collected from 304 employees in the manufacturing industry, software development department. An intelligent mobile application was developed to manage and classify mental workload. Ensemble learning algorithms were used for mental workload classification, among which Hard Voting Ensemble Model outperforms the other techniques with 0.97 accuracy. Based on the findings, the most variable factor of mental workload is psychological factors with a median of 3.25, suggesting that individual differences or specific psychological conditions can significantly affect mental workload. Regarding personalization for managing chronic diseases, the mental workload variables may be utilized to individually adjust digital treatments to the specific requirements of every patient in a person-centered care.

Keywords: mHealth · Mental workload · Digital care pathway · Machine learning · Lifestyle chronic disease

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1 Introduction

1.1 Background and the Aim of the Study

Healthcare is changing from a paternalistic healthcare model to a more proactive care, and finally predictive care. It this new paradigm, the patient is at the center of care, surrounded by various technological solutions that empower them, supporting awareness of factors influencing their health and well-being [1]. This change aligns with the World Health Organization's (WHO) digital health strategy (2021) [2], advocating for putting people at the center of care through the adaptation and utilization of digital health technologies. This patient-centered approach is also referred to as person-centered care (PCC), emphasizing the ongoing interaction in healthcare between the individual and their healthcare team, with support from digital health technologies [3].

Care pathways (also known as clinical pathways or care maps) are treatment plans describing all desired diagnostic and treatment steps to guide and ensure standardized and evidence-based healthcare [4]. By adapting and utilizing digital health technologies, there are opportunities to personalize care pathways more according to the individual patient's needs. The development of tools, such as a personalized healthcare pathway (PHP) [5], an eHealth care pathway that is tailored to the needs of patients with lifestyle chronic diseases [6] and a personalized digital care pathway (PDCP) tool that facilitates tailored information provision [7], are examples of how care pathways can be personalized through the adoption and utilization of digital health technologies.

There is some evidence suggesting that patients can be positive towards the use of different digital health technologies at all stages of their care pathway [8]. These technologies can offer support in personalizing care pathways by providing data to support individuals in adopting healthier lifestyles [6]. In addition, digital health can serve as an additional data source, complementing clinical data. Integrating digital narrative elements from patients into clinical data has shown promising results in conditions like epilepsy, where connecting the clinical perspective with the personal experience of patients has traditionally been challenging [9].

In healthcare, there is an increasing need to address both the mental and physical needs of individuals [10]. Especially in the case of chronic lifestyle diseases, the high mental workload and stress may impact on handling the condition. However, there is still a lack of a consistent, trustworthy, and broadly applicable framework for integrating mental workload into the care pathway for providing sustainable care [11, 12].

This study aims to explore how intelligent mental workload management mobile applications can be integrated to personalized digital care pathways for lifestyle chronic diseases. Specifically, our focus had two primary aspects: firstly, in identifying and establishing factors to assess mental workload, and secondly, exploring how these factors can serve as a complementary data source to contribute to personalization of care pathways. Our research question is: What are the factors related to mental workload, and in what ways can they support the personalization of care pathways?

The rest of the paper reviewed the connection between mental workload and personalization for digital care pathways related to lifestyle chronic diseases. Then the proposed method including the details for system design, multidimensional personalized tool, and the classification of mental workload are presented. Afterwards, the results and analysis section, which consists of multidimensional personalization tool, the effects of different factors on mental workload, mental workload classification using machine learning, and system implementation and interface are reported. Finally, the paper is wrapped up with discussion and conclusion.

1.2 Mental Workload Assessment and Lifestyle Chronic Diseases

The Belgian Health Interview Survey (BHIS) examined the relationship between a healthy lifestyle and mental health outcomes [13]. Assessing and predicting mental health aspects, including psychological distress, vitality, life satisfaction, self-perceived health, depressive and generalized anxiety disorders, and suicidal ideation have significant impacts on the management of lifestyle chronic diseases. Healthy lifestyle habits are positively associated with mental health and well-being [13–20].

High mental workload in employees may potentially affect the onset and management of lifestyle chronic diseases [21]. Chronic mental stress can lead to unhealthy behaviors like poor diet, physical inactivity, smoking, and alcohol use, which are risk factors for diseases like heart disease, diabetes, cancer, obesity, and hypertension [16, 21, 22]. Prolonged stress may also directly impact physiological processes, exacerbating these conditions. Moreover, mental workload can affect sleep patterns and recovery, further influencing the development and management of chronic diseases [22]. Employers should consider these factors in their workplace health strategies.

1.3 Personalization and Digital Care Pathways

Personalization is a key component in PCC, emphasizing the empowerment of individuals to acquire the knowledge, skills and confidence they need for managing and making informed decisions about their health. It promotes the concept of active individual in managing their health, surrounded by healthcare professionals who use digital health technologies to complement the individual's resources, fostering the creation and exchange of health-related knowledge between the individual and the healthcare professional [23]. The development of digital health technologies provides new opportunities to enhance individual awareness of factors influencing their health and wellbeing [1]. Various technologies such as sensors and wearables can continuously provide real-time data about the individual, contributing to personalization related decision-making in care [24].

Digital health technologies have the potential to serve as a data source for supporting the personalization of care pathways [6, 9]. This support can vary from technology-driven automated assistance to a more collaborative approach involving data-driven decision-making [25]. There is a growing interest in developing tools and solutions for personalized care pathways. A personalized digital care pathway (PDCP) was introduced by [7], serving as a digital tool offering healthcare professionals and patients an overview of a personal care pathway, displaying adequate and dosed information gradually as the care pathway progressed. The information tailored to the individual serves as the foundation for collaborative decision making in care, fostering a more person-centered approach throughout the care process. In [9] narrative medicine methodologies were integrated into clinical practices using a digital platform. Patient narratives collected digitally were integrated with the clinical data to personalize the care pathway for individual patients. Both healthcare professionals and patients could benefit from these data as digital interactions allowed patients to share important aspects of treatment plans, such as more personal and emotional experiences of their condition, which may be challenging to express in the traditional healthcare setting. Furthermore, a personalized eHealth care pathway specifically tailored for patients with lifestyle related chronic diseases, supporting patients in making psychological and lifestyle adjustments was introduced by [6]. This care pathway tool automatically detected increased risk profiles but also provided personalized support to help patients to actively adopt a healthy lifestyle with a focus on psychological and lifestyle-related assistance.

Integrating mental workload management into personalized digital care pathways can significantly enhance healthcare delivery by tailoring treatments to individual patient needs while also ensuring that healthcare providers operate efficiently and without extreme cognitive burden. By incorporating mental workload management, digital care pathways can provide decision support that is tailored not just to the patient's needs, but also to the specific context and capabilities of the healthcare provider. For instance, a system might offer more focused guidance to a patient under high workload conditions, thus ensuring that patient care and well-being are optimized [26–28].

2 Method

2.1 System Design and Modules

The proposed mobile application two-tier architecture diagram is illustrated in Fig. 1. The first layer is the presentation tier where it corresponds to the client-side of the mobile application built with React Native. It handles the user interface, user interactions, and rendering of the application on the mobile device. The second layer is a data tier which consists of the backend components that interact with data and external services. The proposed AI-Mental application utilizes Flask as the web framework hosting the machine learning model, Firebase as the database for storing and managing data, and integration with the ChatGPT API for incorporating conversational AI capabilities. The main users for this application are employees and employers in the manufacturing workplace. The main input of the mobile application is the mental workload assessment provided by the users, which is used to predict employee mental workload. The employee mental workload record, results of the mental workload assessment and classification will be displayed on the dashboard as the main output of the system.

AI-mental consists of four main modules including: (1) account management module, (2) assessment module for data collection, (3) ensemble learning module for data analytics, and (4) dashboard or visualization module. The account management module is responsible for registering new accounts, login, updating profiles, and managing employee accounts whereas assessment module main task is collecting mental workload data from the users. Ensemble learning module is designed to classify mental workload, generate advice and suggestions based on the use status. Dashboard module, as the main output of the system, displays user profile, visualizes the mental workload prediction results and advice, and generates a summary for the employers. AI-mental mobile application provides user interface for all modules, which allows user to understand and interact with the system.

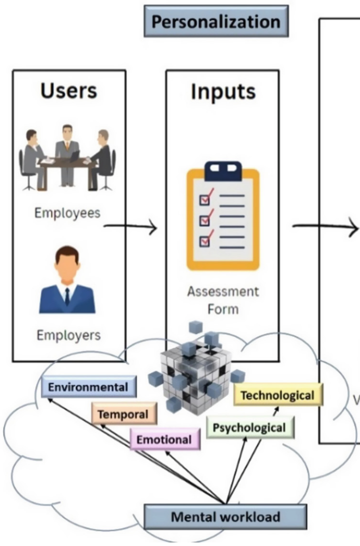

Fig. 1. Overall Architecture Diagram for Mental Workload Mobile Application.

2.2 Process to Design a Multidimensional Personalization Tool for Assessing Mental Workload

In order to classify mental workload, different types of data can be utilized. In this study, we have decided not to use the mental workload classification method based on physiological and performance-based techniques. The physiological technique, which requires specialized EEG measurement devices and experienced professionals to conduct the EEG test, is not preferred due to its high cost and complexity. Similarly, the performance-based technique is not ideal as it is not sufficiently sensitive to workload changes, and the measurement of secondary tasks may compromise the accuracy of the results. Therefore, this study will solely implement the subjective technique, specifically the self-assessment method.

This study aims to integrate mental workload related factors from patients into digital care pathways to provide personalized care specially for lifestyle chronic diseases. Therefore, a multidimensional personalization tool is designed in this study to improve mental well-being in digital care pathway. Furthermore, the study goal is to classify mental workload using machine learning techniques based on the data collected from multidimensional personalization tool or questionnaire. For this reason, the proposed questionnaire was distributed to individuals with employee roles. The existing self-assessment tools are compared in terms of dimensions, rating scale, strengths, and weaknesses as shown in Table 1.

Table 1. Comparison of Existing self-assessment tools.

Self-assessment Technique	Dimensions	Rating Scale	Strengths	Weaknesses
Carga Mental Questionnaire (CarMen-Q)	Cognitive, Temporal, Emotional, Health, and Performance Demands	0 to 3	- The technique does not include physical demands as it is not practical in measure mental workload - Identifies areas where individuals may be experiencing high levels of mental workload - Allows interventions to be implemented to reduce stress and improve performance	- Relies on self-report, which may be influenced by individual biases and perceptions - Does not measure all aspects of mental workload such as social demand
NASA task load index (NASA-TLX)	Mental demand, Physical demand, Temporal demand, Effort, Performance, and Frustration level	0 to 20	- The technique can be applied to a variety of domains due to its multidimensional and generic measurement property - It is relatively easy to administer and can be completed in a short amount of time	- Requires the participants to complete during their work which may not be feasible in certain situation such as high-stress environment - Result might be influenced by personal factor such as stress, fatigue, and motivation - Not be sensitive enough to capture small changes in workload over time, or to distinguish between different levels of workload within a single task
Subjective Workload Assessment Technique (SWAT)	Time Load, Mental Effort Load, and Psychological Stress Load	1 to 3	- Identifies potential areas for improvement or delegating tasks to better distribute workload - Provides a more personalized and accurate assessment of workload for individual employees	- Not very sensitive for low workload conditions - Requires a time-consuming pre-task card sorting procedure

Different existing tools or questionnaires were considered to propose the multidimensional personalization tool for this study. Some of the existing self-assessment techniques that used by the previous research papers including Depression Anxiety and Stress Scale 21 (DASS-21) [29], Carga Mental Questionnaire (CarMen-Q) [30], NASA Task Load Index (NASA-TLX) [31], Subjective Workload Assessment Technique (SWAT) [32], Cooper-Harper Rating Scale [33] and more. Among those questionnaires used for assessing mental workload, the most popular subjective techniques used are the Carga Mental Questionnaire (Carmen-Q), NASA Task Load Index (NASA-TLX), and Subjective Workload Assessment Technique (SWAT).

After the comparison of existing tools, the proposed multidimensional personalization tool was designed, and the dimensions were selected. The proposed tool was reviewed and verified by an expert in psychoanalysis from the School of Humanities. Then the questionnaire was used for data collection and the pilot study. 304 responses were received from the employees in the manufacturing industry, the software development unit, providing valuable data for the analysis and classification of mental workload levels.

2.3 The Process Flow of Mental Workload Classification

The main objective of ensemble module was the classification of mental workload using machine learning techniques based on the data collected from multidimensional personalization tool or questionnaire. Figure 2 illustrates the step-by-step process of training the machine learning model. First, several preprocessing techniques have been applied to the dataset to ensure its quality and suitability for analysis such as checking missing values, verifying the presence of any invalid responses for both inputs and output. Next, the inputs and outputs of the dataset were converted to integer format to facilitate their utilization in training machine learning models. The pre-processed dataset is then divided into 80% train data and 20% test data. Since the dataset contains imbalanced classes, the Synthetic Minority Oversampling Technique (SMOTE) was implemented for classification. It is important to note that SMOTE was applied only to the training data and not the test data to prevent overfitting. By applying SMOTE to the training data, the minority class instances are oversampled to balance the class distribution. This helps to mitigate the impact of class imbalance and ensures that the machine learning model is trained on a more representative dataset.

Furthermore, the machine learning models are trained and evaluated using various classification algorithms. The models selected for evaluation include K-Nearest Neighbors (KNN), Decision Tree, Support Vector Machine (SVM), Logistic Regression, and Naive Bayes. Each model is fitted to the training data using their respective algorithms. The evaluation results for each model are calculated, showcasing their precision, recall, F-1 score, and accuracy scores. Logistic regression model shows a relatively poor performance based on the evaluation results. After that, hyperparameter tuning using GridSearchCV is performed to optimize the models' performance by finding the hyperparameter settings that yield the highest accuracy or other evaluation metrics such as precision, recall, or F-1 score. This helps to fine-tune the models and improve their predictive capabilities on the given dataset. The best hyperparameters are shown in the figure below. The machine learning models are then trained and evaluated using the hyperparameters.

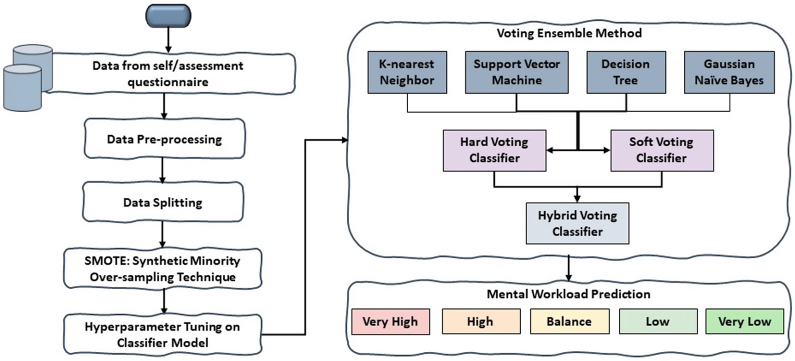

Fig. 2. Process Flow of the Proposed Mental Workload Classification Model using Ensemble Learning.

3 Results and Analysis

3.1 Multidimensional Personalization Tool

This study aims to design a personalized digital care pathway by integrating mental workload related factors for patients with lifestyle chronic diseases. Therefore, a multidimensional personalization tool is designed in this study (Fig. 3) to improve mental well-being in digital care pathway. The proposed multidimensional personalization tool illustrates various dimensions of overall mental workload, which is defined as the total cognitive burden placed on an individual at a given time, encompassing all cognitive processes required to perform tasks. Assessing overall mental workload involves considering both the demands imposed by the task and the individual's capacity to handle these demands, taking into account their skills, experience, and current psychological state.

Incorporating factors like Environmental, Psychological, Technical, Emotional, and Temporal into understanding and managing mental workload can significantly enhance the personalization of care pathways. A clinical understanding of the impact of physical and social environments on an individual's mental workload can lead to personalized interventions. This might include modifying lighting, noise levels, or even the arrangement of living or working spaces. Tailoring work of living environments to reduce unnecessary stressors or distractions. For example, providing a quiet and comfortable space for someone who is easily overstimulated by noise or crowding.

Recognizing personal psychological traits such as resilience, anxiety levels, or coping mechanisms can help predict how individuals handle mental workload. Developing stress management or resilience training programs tailored to the individual's psychological profile. For example, providing cognitive-behavioral therapy for someone prone to anxiety or stress. Identifying how comfortable and efficient individuals are with the technology and tools they use daily can influence their mental workload. Offering training or tools better suited to an individual's technical skills and preferences or redesigning workflows to reduce technical burdens. Considering the emotional states and variability in how individuals emotionally respond to stressors can inform care pathways. Integrating emotional support structures, counseling, or techniques like mindfulness and emotional regulation strategies tailored to how the individual experiences and processes emotions.

Recognizing the effects of time pressure, deadlines, and the pacing of activities on mental workload is crucial. Adjusting schedules, setting realistic deadlines, or creating time management plans that accommodate an individual's pace and workload capacity is useful for mental workload management. Continuously assessing mental workload allows for dynamic adjustments in care and support strategies, ensuring they match the individual's current needs. Implementing adaptive interventions that respond to real-time assessments of mental workload, perhaps using wearable tech or self-reporting tools for immediate feedback.

Combining insights from all factors of mental workload assists us to understand the multifaceted nature of an individual's experience, which involves creating a comprehensive profile that considers all dimensions. Regularly monitoring each factor's impact and adjusting the care pathway is needed to include routine assessments and the flexibility to change strategies as the individual's situation or responses evolve. Engaging the individual in understanding the mental workload factors and incorporating their preferences and feedback into the care pathway design is suggested to enhance the current digital care pathways. This ensures the solutions are not only personalized but also embraced by the individual. By considering these factors as parameters of personalization, care pathways can be more effectively tailored to each individual, enhancing the likelihood of successful outcomes, improving engagement, and reducing the overall mental workload. This holistic and nuanced approach ensures that interventions are not only technically sound but also resonate with the individual's unique circumstances, preferences, and needs.

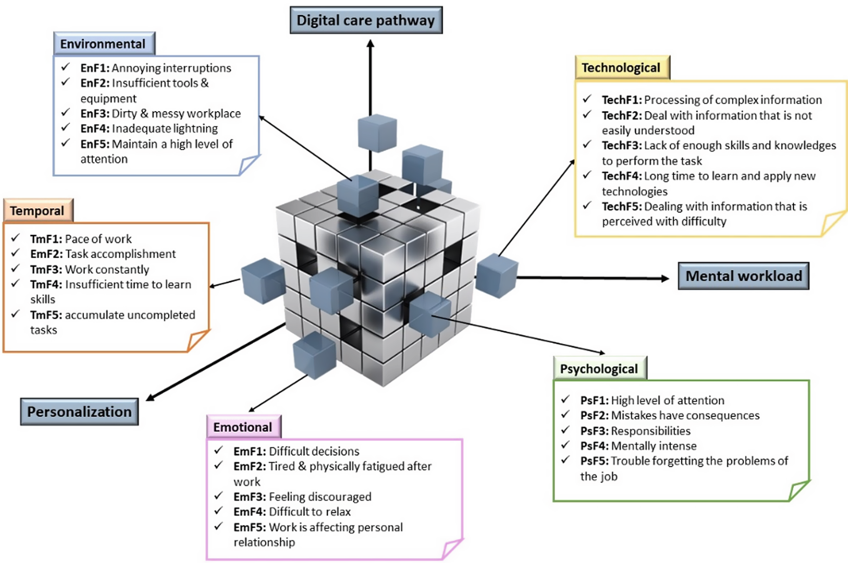

Fig. 3. Multidimensional Personalization Tool to Improve Mental Well-being in Lifestyle Chronic Diseases Digital Care Pathway.

3.2 The Effects of Different Factors on Mental Workload

Figure 4 shows the data distribution of the factors based on the collected data. For the Environmental Factors (EnF), the median is at 3.5, suggesting a moderate impact on mental workload. The narrow interquartile range (IQR) implies that the Environmental Factor's impact on mental workload is relatively consistent among the subjects or conditions tested. The absence of outliers indicates that extreme conditions of the environmental factor are either not present or do not significantly deviate from the typical impact on mental workload. However, the median for Psychological Factor (PsF) is slightly lower than EnF at 3.25, suggesting a slightly less overall impact on mental workload. The wide IQR, however, indicates that the impact of PsF on mental workload varies more significantly among individuals or situations than the Environmental Factor does. The presence of an outlier at a low value indicates that there may be certain psychological conditions or events that can extremely reduce mental workload.

With a median above 3.5, Technological Factor (TechF) might have a slightly higher impact on mental workload compared to Environmental and Psychological Factors. The moderate IQR suggests some variability in how different technological factors influence mental workload but less so than Psychological Factors. No outliers suggest that extreme technological factors are not significantly different in terms of their impact on mental workload. The median for Emotional Factor (EmF) is around 3.25, which is similar to the Psychological Factor, suggesting a comparable level of impact on mental workload. The IQR is not as wide as for PsF, which indicates that while Emotional Factors affect mental workload, the degree of this impact may be more predictable and less variable than Psychological Factors. The lack of outliers suggests that extreme emotional conditions do not commonly occur or do not significantly deviate from the typical impact range.

The Temporal Factor (TmF) has a median just below 3.5, indicating a moderate impact on mental workload. The very narrow IQR suggests a highly consistent impact of Temporal Factors on mental workload across different conditions or subjects. The absence of outliers implies that even when time constraints or pressures are irregular, they do not have an unusually high or low impact on mental workload.

3.3 Mental Workload Classification Using Machine Learning

As shown in Table 2, four different algorithms including k-nearest neighbors algorithm (k-NN), decision tree, support vector machine (SVM), and Gaussian Naive Bayes (GNB) are selected and compared in terms of performance. Since data was imbalanced, SMOTE was utilized as the oversampling technique and the results are compared before and after applying it. In this study, two voting classifiers are initialized: a hard voting classifier and a soft voting classifier. Both classifiers employ k-nearest neighbors algorithm (k-NN), decision tree, support vector machine (SVM), and Gaussian Naive Bayes (GNB) as estimators. They are trained on the resampled training dataset and their performance is evaluated using cross-validation. Subsequently, these classifiers are applied to make predictions on the test dataset, and performance metrics including accuracy, precision, recall, and F1 score are calculated for both. Additionally, a final voting classifier is created by combining the hard and soft voting classifiers. This final classifier is then used for predictions on the test dataset.

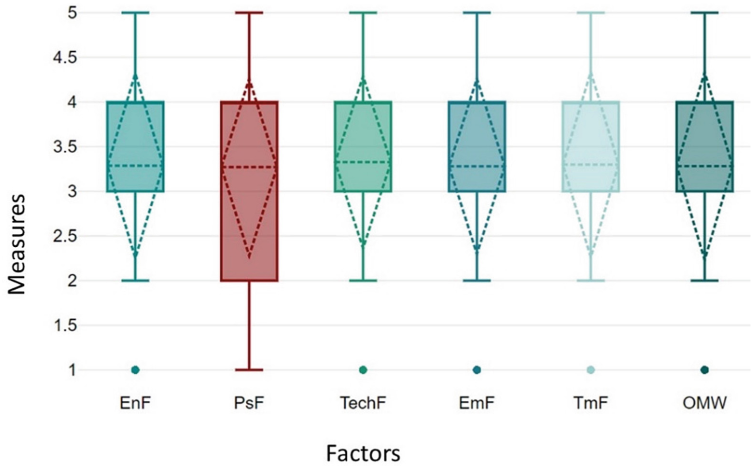

Fig. 4. Data Distribution for Mental Workload Variables.

Table 2. Performance Comparison of Different Machine Learning Techniques.

Machine Learning Model	Precision		Recall		F-1		Accuracy	
	Before	After	Before	After	Before	After	Before	After
KNN	0.86	0.96	0.80	0.87	0.87	0.93	0.87	0.93
Decision Tree	0.94	0.94	0.81	0.81	0.89	0.89	0.90	0.90
Support Vector Machine	0.94	0.97	0.87	0.82	0.92	0.91	0.92	0.91
Naive Bayes	0.90	0.90	0.80	0.80	0.84	0.87	0.89	0.89
Hard Voting Ensemble Model	0.93		0.92		0.91		0.97	
Soft Voting Ensemble Model	0.93		0.92		0.91		0.96	
Hybrid							0.92	

3.4 System Implementation and User Interface

Agile development methodology is selected for this study as it allows developers to deliver high-quality products faster, with greater flexibility and collaboration. It enables the developers to adapt quickly and to respond to new or changing features during development. Furthermore, it mainly concentrates on the deliverables and involves less planning than other traditional methodologies [15, 34, 35]. Therefore, it is suitable for AI-mental application due to the short timescale.

The proposed employee mental workload management application has adopted a top-down approach as its implementation strategy. This choice was made because the system was developed from scratch, requiring a generalized system model during the initial stages of design and implementation. To achieve this, the system was divided into four main modules: (1) Employee Management Module, (2) Assessment Module, (3) Ensemble Learning Model Analytics Module, and (4) Result Visualization Module.

Each of these modules was further broken down into smaller fragments until reaching the lowest hierarchy level, which provides more detailed functionalities. This approach of breaking down a larger problem into smaller components helps to reduce complexities that typically arise during the design and implementation phases. Additionally, it facilitates independent testing and debugging of each module since they can be evaluated individually.

The main programming languages used for development were Javascript, Python, and SQL. Firebase was used for database development. React.js (Front-end), Node.js (Back-end), and Flask (Machine Learning Model Hosting) were utilized as the main framework for the application development.

Figure 5 depicts the user interface for the proposed intelligent mental workload management mobile application.

Fig. 5. User Interface for The Developed Personalized Mobile Application.

The login screen serves as the landing page. Users without an account can register via the Sign-Up Screen. After logging in, employees are directed to the Home Screen, which offers access to various screens through the navigation bar and users can update their profile. As for the assessment screen, users who haven't completed their daily assessment will see the screen. Those who have completed it will see another screen. The assessment consists of six screens, each with five questions. Assessment results will be shown in the Result Screen, and past results can be accessed on the History Screen and the history of mental workload assessment for the last week or month will be displayed in the history screen.

Furthermore, a visualization presenting assessment data in graphs and statistics will be depicted in the visualization screen. Employers are presented with a home screen and can manage employees using the Management Screen. This screen allows access to employee information, and the ability to delete or add employees. The Add New User Screen for adding new employees is part of the management screen. To monitor the mental workload of employees, employers use the Tracker Screen. They also have access to employee assessment results, visualizations, and assessment history. For an overview of employees' mental workload, the overall visualization screen will be displayed.

3.5 The Proposed Personalized Process for Lifestyle Chronic Disease Care Pathway

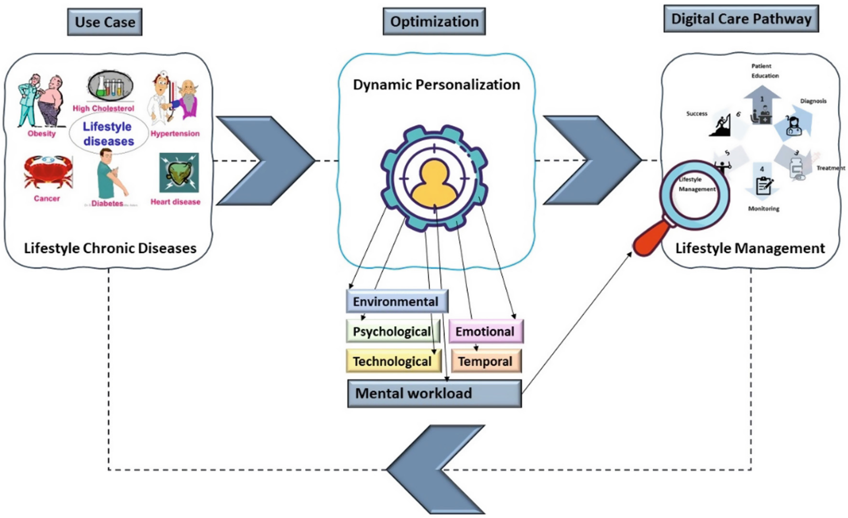

Fig. 6. The Proposed Iterative Process for Personalized Care Pathway for Lifestyle Chronic Disease.

Based on the results illustrated in Fig. 4, we can infer that while each factor has a moderate and consistent impact on mental workload, there are some differences. For instance, Psychological Factors show the most variability, indicating that individual differences or specific psychological conditions can significantly affect mental workload. Technological Factors show a slightly higher median impact, which could be due to the challenges of using new or complex technologies. Temporal Factors have the least variability, suggesting that time-related pressures are a consistent and predictable source of mental workload. Environmental and Emotional Factors appear to have a moderate and consistent impact on mental workload.

We propose that these mental workload related factors can serve as a complementary data source, enhancing the personalization of care pathways. They take into account various aspects of an individual's mental workload, emphasizing the importance of understanding the person as a whole. In Fig. 6 an iterative process for personalized care pathway for lifestyle chronic diseases is proposed. In the use case of lifestyle chronic diseases, the personalization process is dynamic, considering the factors that all contribute to an individual's lifestyle management within the care pathways, aiming to improve the mental well-being of an individual.

4 Discussion and Conclusion

This study investigated the factors related to mental workload, and the way they can support the personalization of care pathways specially for lifestyle chronic diseases. It proposes five factors: Environmental, Psychological, Technical, Emotional, and Temporal and examines how these factors can serve as parameters of personalization in care pathways. Taking these factors into account may enhance the personalization of care pathways for individuals, thereby increasing the likelihood of successful outcomes, improving engagement, and reducing the overall mental workload.

The multidimensional personalization tool presented in this study offers insights into mental workload related factors, with the aim of enhancing the individual's mental well-being within the digital care pathway. Given the growing importance of addressing both the mental and physical needs of an individual in healthcare [36], which is especially important in the case of chronic lifestyle diseases [6] the findings of this study align with the previous literature that considers on psychological and lifestyle-related factors in the personalized eHealth care pathways, targeted for patients with lifestyle-related chronic diseases [6].

The results illustrated in Fig. 4 suggest that when considering interventions to manage mental workload, attention should be given to the variability within Psychological Factors, as this is where individual differences are the most noticeable. Technological Factors may need to be closely monitored and managed to prevent an increase in mental workload. Temporal Factors, while consistent, should not be overlooked as they still contribute to the overall mental workload.

Since the environmental factor has a consistent but moderate impact on mental workload, digital care pathways can be personalized by considering the patient's environment. For example, the interface and notifications can be tailored to be less intrusive if a patient is in a stressful environment.

The high variability and the presence of outliers in psychological factors suggest that mental workload is significantly influenced by personal psychological conditions. Personalization in this aspect could mean incorporating cognitive-behavioral strategies, stress management, and coping mechanisms into the digital care pathway. This can help in providing a more tailored approach to managing psychological stressors that affect chronic disease management.

With technology having a slightly higher median impact on mental workload, digital care pathways need to be intuitive and user-friendly. Personalization could involve adapting the technology to the user's proficiency, providing training modules, or simplifying the user interface to reduce cognitive load.

Emotional factors affect mental workload to a degree like psychological factors but with less variability. Digital care pathways can incorporate features that monitor mood and provide emotional support, such as through motivational messages or alerts to seek human support when needed.

Temporal factors show a consistent impact on mental workload, indicating the importance of time management in chronic disease care. Personalization could involve scheduling medication reminders, appointments, and activities at times when the patient is less likely to be stressed.

Finally, digital care pathways should aim to distribute the mental workload evenly, avoiding overwhelming the patient. This can be achieved by decreasing the information overload on patient or reducing the tasks at once and by providing a personalized schedule that considers the patient's daily routine and capacity.

In relation to personalization for chronic disease management, these factors can be used to tailor digital interventions to each patient's unique needs in a person-centered manner. For instance, the platform can have *adaptive content*. It could adjust the information complexity based on the user's current cognitive load and emotional state. Furthermore, *user-centered design* can be considered. Interfaces can be designed considering the user's technological proficiency to avoid additional stress or workload. *Behavioral tracking* is another feature that can be incorporated into the care pathway to track psychological and emotional status to adjust the care plan. *Context-aware notifications* and reminders could be sent considering the patient's environment and time constraints to avoid adding stress. Integrating *stress management tools* for relaxation and stress relief can manage emotional and psychological factors that contribute to mental workload. *Support systems* facilitate access to support groups or counseling through the digital pathway that can address emotional and psychological needs. Finally, personalizing digital care pathways in these ways can help in managing the overall burden on patients with chronic diseases, leading to better engagement, adherence, and potentially better health outcomes.

Moreover, based on the results of this paper, we suggest conceptualizing an iterative personalized digital care pathway for lifestyle chronic diseases, as illustrated in Fig. 7. The iterative personalized digital care pathway emphasizes a holistic approach to care. This involves addressing diagnosis and treatment aspects, but also incorporating patient education and lifestyle management. Mental workload related factors play an important role, particularly in the lifestyle management of individuals. This aligns with the research from [6] where personalized support was provided to patients to actively adopt healthier lifestyles. By incorporating data on mental workload assessment, we believe there is an opportunity to increase individuals' awareness of the factors that can influence their health and well-being [1]. Also, the adoption and integration of digital health technologies offers possibilities to empower the patient. When combined with other data sources and care collaboration with healthcare professionals, these aspects can enhance the personalization of care pathways for individuals.

If employees' mental workload is managed effectively, it can contribute to lifestyle behaviors and conditions that elevate the risk of chronic diseases. Therefore, workplace health promotion programs are vital in mitigating these risks and fostering a healthier, more productive workforce.

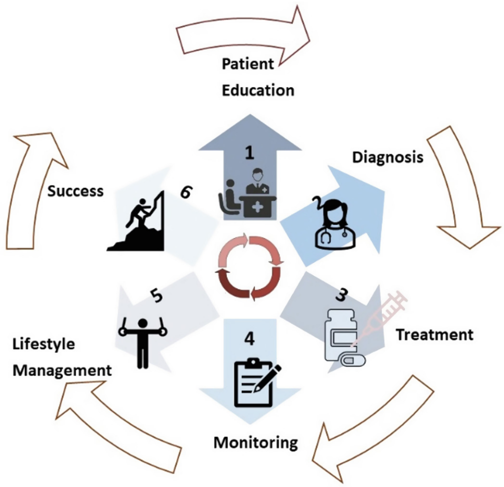

Fig. 7. Conceptualizing an Iterative Personalized Digital Care Pathway for Lifestyle Chronic Diseases.

Limitations. This study has some limitations. An expert in psychoanalysis reviewed and verified the suggested multidimensional personalization tool. However, integrating the tool with the clinical data was beyond the scope of this paper. Previous literature provides examples of incorporating data generated by digital health solutions into clinical data to personalize care pathways [9]. In this paper, we believe that the introduction of a multidimensional personalization tool and established factors for assessing mental workload can serve as a starting point for exploring the integration of this tool with clinical data in the future.

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