Developing a Digital Mental Health Ecosystem for Workplaces: Rationale, Objectives, and Methods of the MetrikaMind Project

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Abstract

Background: Depression and anxiety are among the leading causes of disability worldwide, significantly impacting workplace productivity through absenteeism and presenteeism. The MetrikaMind platform offers a scalable, digital solution for addressing these challenges by providing personalized, AI-driven mental health assessments and real-time monitoring in workplace settings. **Methods:** This one-arm pre-post study will recruit 1,000 participants from the general population and 600 participants from a sick leave population in Spain. The primary outcomes will assess changes in depression and anxiety symptoms using validated tools, with weekly assessments for up to 6 months. Secondary outcomes include measures of personality, workplace engagement, and perceived occupational stress, alongside platform engagement metrics. Data will be analyzed using bifactor models to account for response biases such as social desirability and to predict mental health outcomes more accurately. **Ethics:** The study complies with the Declaration of Helsinki and Oviedo Convention. Informed consent will be obtained, and data confidentiality will follow GDPR standards. The protocol has been approved by the Institutional Review Board (IRB 00003099). **Discussion:** MetrikaMind is expected to improve the accuracy of mental health assessments in the workplace, reducing response biases and enabling earlier detection of changes in anxiety and depression symptoms. The platform's predictive capabilities may also lead to innovations in workplace mental health policies and interventions. This project has the potential to improve employee well-being and workplace productivity by offering precise, real-time mental health assessments. The platform's integration of active and passive data sources enhances its ability to provide tailored, effective support, setting the foundation for future digital mental health innovations. **Trial Registration:** ClinicalTrials.gov Identifier: NCT06650176

Background

Mental health problems, particularly anxiety and depression, are leading causes of disability worldwide, affecting over 280 million people with depression and 264 million with anxiety (1). These conditions contribute significantly to the global disease burden, reducing productivity and increasing absenteeism and early retirement. The global cost of depression and anxiety is projected to reach USD 6 trillion by 2030, including healthcare costs and lost productivity (2). In Europe, mental health issues account for 4% of GDP, or €600 billion annually, with €240 billion attributed to productivity losses alone (3,4). Addressing mental health in the workplace is not only a public health imperative but also an economic necessity. While the economic burden of mental health issues is clear, the path to resolving these challenges often begins with access to care, which remains elusive for many workers.

Among the causes that impede access to mental health are long waiting times, stigma, and high costs. In many countries, public health systems are overwhelmed, leading to delays of up to six months for psychological consultations, which can be particularly detrimental for individuals with anxiety and depression, where early intervention is critical (5). Furthermore, stigma surrounding mental health continues to be a major deterrent, with many workers fearing they will be perceived as weak or unreliable (6). These challenges often compound financial barriers, creating an additional layer of difficulty in accessing care. In Eastern European countries like Romania and Slovakia, workers must dedicate over two days' wages for a single therapy session, while in Western Europe, a few hours' wages are sufficient (5). This disparity highlights how both stigma and financial burden work in tandem to limit access to essential mental health services across Europe, leaving many employees unsupported (7). The direct consequence of these barriers to access is reflected in the profound impact of mental health conditions on workplace productivity and performance.

Companies facing these challenges often experience reduced profitability and competitiveness due to higher absenteeism, presenteeism, and diminished employee morale (8). Depression and anxiety reduce focus, decision-making ability, and cognitive function, directly affecting an employee's ability to complete tasks efficiently. Depression alone can result in a 35% reduction in task completion (9), while mental health issues account for 50% of long-term absenteeism in Europe (10). Thus, addressing mental health in the workplace is critical for maintaining a productive and engaged workforce as these issues continue to rise (11). In response to these rising challenges, digital health platforms have emerged as promising solutions to bridge the gap in assessment and treatment.

The global rise in mental health disorders, accelerated in the last years by the COVID-19 pandemic, has underscored the need for innovative solutions like digital health platforms to bridge the gap in assessment and treatment. These platforms offer scalable, accessible, and cost-effective interventions that can reach a broader population than traditional in-person services(12). However, most digital tools are focused on intervention rather than assessment (13). AI-driven solutions, such as chatbots and algorithms, can provide real-time monitoring and early intervention for anxiety and depression, with platforms like Woebot demonstrating efficacy in clinical trials (14). However, while the success of these tools in providing treatment is apparent, the field has largely neglected the potential for these technologies to enhance the accuracy and depth of mental health assessments (15). Incorporating advanced assessments, alongside intervention tools, could significantly improve personalized mental health care, offering more precise insights into individuals' needs before treatment even begins (16). Despite the advancements in treatment tools, the need for robust mental health assessments remains underaddressed in digital health solutions (17,18).

Programs like the UK's Talking Therapies (formerly IAPT) highlight the importance of incorporating routine assessments into mental health care. By integrating validated psychological assessments into primary care, Talking Therapies has shown that regular monitoring improves mental health outcomes and tailors interventions more effectively (19). This approach underscores the need for assessment in digital mental health care, but many platforms still lack evidence-based tools. Few have undergone rigorous trials or demonstrated long-term efficacy (18). Additionally, unvalidated self-report surveys, commonly used by apps, often fail to capture the complexity of mental health disorders like depression and anxiety. Moreover, even validated programs like Talking Therapies miss the nuances of depression and anxiety, which highlights the broader issue of insufficient mental health assessment practices (20), although this is gradually changing.

In addition, many digital platforms overlook the critical issue of response distortions, which can be broadly categorized into non-deliberate and deliberate distortions. Non-deliberate distortions include tendencies like social desirability, where individuals unconsciously present themselves in a socially acceptable light, or response patterns such as acquiescence and extreme responding (21). For instance, a participant may agree with items due to acquiescence rather than reflecting their true mental state. Deliberate distortions, on the other hand, involve intentional manipulations like impression management, "faking good," or "faking bad" (22). Both types of distortions—non-deliberate (such as social desirability or acquiescence) and deliberate (such as impression management or faking)—can severely skew assessments and lead to improper interventions. This is particularly concerning in workplace settings, where evaluations can have high-stakes consequences, such as decisions about job security or sick leave (23). Thus, developing more precise assessment tools that can accurately account for and correct these biases is critical to ensuring effective mental health interventions and decisions. This challenge becomes even more critical in workplace environments, where mental health assessments must account for unique stressors and high-stakes consequences.

Work environments present unique challenges in managing mental health, with employees often experiencing anxiety, depression, and stress exacerbated by high performance expectations, deadlines, and interpersonal conflicts (24). These pressures are compounded by workplace stigma, where employees may fear that disclosing mental health struggles could jeopardize job security or career advancement. In these settings, the potential for AI-driven real-time monitoring becomes particularly valuable. By continuously assessing and flagging changes in mental health, such platforms can identify at-risk employees earlier, allowing for timely and tailored interventions that address mental health challenges before they escalate (25). This stigma, coupled with the underreporting of mental health issues, makes accurate workforce assessments difficult. Moreover, presenteeism—where employees are physically present but not fully productive—often goes unnoticed, further affecting productivity (26). Most workplace interventions are generalized, lacking customization for the specific pressures employees face (27). Effective mental health solutions should focus on precise assessments and early detection, leading to improved employee well-being, increased engagement, reduced turnover, and enhanced organizational performance. MetrikaMind seeks to address these workplace-specific challenges by introducing an innovative platform designed to provide precise assessments and real-time monitoring of anxiety and depression.

By integrating evidence-based assessments, AI-driven algorithms, and psychometric tools to detect response biases such as social desirability, "faking good", or "faking bad," the platform provides personalized, real-time insights into employee mental health. While not directly treating anxiety and depression, MetrikaMind focuses on offering a precise and effective monitoring system, improving early detection of mental health changes, supporting interventions, and enhancing employee well-being, productivity, and organizational performance.

Intervention programs such as the UK's Improving Access to Psychological Therapies (IAPT) have shown that regular mental health assessments lead to significant reductions in anxiety and depression, improving workplace outcomes (28). Similarly, data-driven platforms like MetrikaMind, with their focus on continuous monitoring and early detection, could provide similar, if not greater, economic benefits by offering real-time insights that help employers address mental health issues before they escalate. Studies estimate a fourfold return on investment in mental health interventions (29), suggesting that MetrikaMind's real-time monitoring could similarly reduce the economic burden on employers. Moreover, MetrikaMind's predictive capabilities could lead to innovations in health insurance, enabling personalized mental health coverage (15). Enhanced accuracy in assessments could also help identify new therapeutic targets, driving progress in personalized mental health care.

Scientifically, the MetrikaMind platform will generate valuable data on the efficacy of digital mental health assessments in workplace settings. While psychological assessment itself can have a therapeutic effect (30), MetrikaMind's use of validated tools, AI-driven assessments, and the ability to detect response biases addresses critical gaps in current mental health diagnostics. Additionally, the project aligns with policy initiatives aimed at integrating digital solutions into mental health strategies (29), highlighting MetrikaMind as a forward-thinking solution to workplace mental health challenges and supporting its core objectives.

Objectives of the MetrikaMind project

The MetrikaMind project aims to develop, using an exploratory framework, an innovative digital mental health ecosystem tailored for workplace environments. The primary and secondary objectives focus on improving the assessment of anxiety and depression in the workforce using advanced technology, psychometrics, and AI.

1. **Primary Objective:**

   To design and implement a digital platform that delivers accurate and reliable assessments of anxiety and depression in workplace settings. Leveraging real-time assessments, AI-driven algorithms, and psychometric tools to detect response biases, the platform facilitates early detection of symptoms' change and supports mental health management, without directly providing treatment.

2. **Secondary Objectives:**

   - **Objective 1:** To develop a structured psychological evaluation system using Key Psychological Indicators (KPIs) identified through factor analysis, focusing on constructs like pessimism, self-criticism, and sadness for individualized mental health assessments.
   - **Objective 2:** To collect both active and passive data, including Ecological Momentary Assessments (EMA) and sensor-based inputs (mobility, physical

activity) to provide real-time insights and generate comprehensive reports (see Figure 1).

- **Objective 3:** To develop and validate AI algorithms to predict the progression of mental health issues, supporting early interventions.
- **Objective 4:** To address response biases, such as “faking good” and “faking bad,” through advanced psychometric strategies to enhance the accuracy of assessments.
- **Objective 5:** To validate the platform's predictive and diagnostic capabilities across diverse groups, ensuring adaptability and effectiveness in workplace and clinical settings.

These objectives aim to enhance the assessment of anxiety and depression in workplaces, addressing response biases and improving early detection, ultimately benefiting both individual well-being and organizational performance.

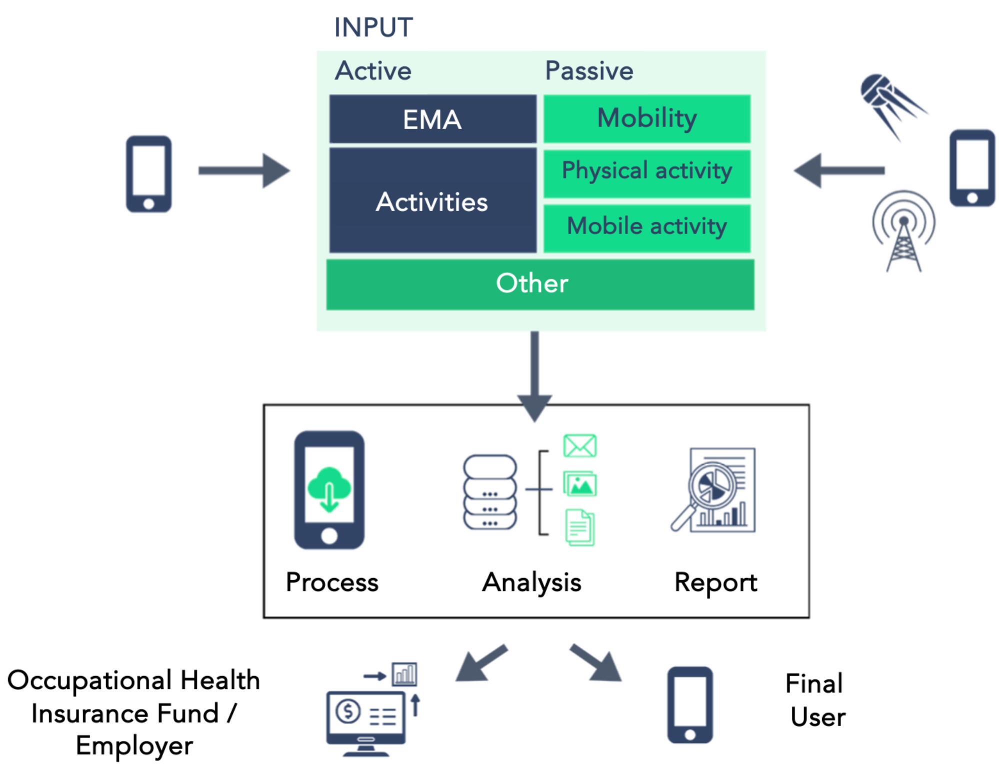

Figure 1: Overview of the MetrikaMind Platform Architecture. The MetrikaMind platform collects input from both *active* and *passive* data sources. Active data includes *Ecological Momentary Assessments (EMA),* and *Activities* reported by the user, while passive data includes *Mobility, Physical Activity*, and *Mobile Activity* captured through sensors. This data is processed and analyzed in real-time, with the results presented in personalized reports. These customizable reports are made available to *the final user* (employees or participants) and, where appropriate, to *Occupational Health Insurance Funds or employers*. The platform aims to provide continuous monitoring and accurate assessment of mental health, offering insights for early intervention and tailored mental health strategies in workplace settings if needed.

Methods of the MetrikaMind Project

Study Design

The MetrikaMind project will employ a prospective, one-arm pre-post design to evaluate the platform's ability to monitor anxiety and depression in workplace settings. Longitudinal data will be collected to fit bifactor models on them, generating personalized predictions and establishing norms for workplace mental health while considering response biases (31). The design follows TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis) guidelines, ensuring robust prediction models for early detection of mental health changes, such as anxiety and depression (32).

Study Population

The study will recruit a diverse sample of adult employees aged 18-65 across various industries in Spain. **Inclusion criteria** are adult employees with access to digital devices (smartphone, computer, or tablet), fluency in the platform’s language, and willingness to participate in regular digital assessments. **Exclusion criteria** include employees currently undergoing intensive psychological treatment or those diagnosed with severe psychiatric conditions (e.g., schizophrenia, bipolar disorder), as these factors may interfere with the study's data collection and focus (33).

We expect to gather data from approximately 1,000 participants from the general population and 600 participants on sick leave, managed by an Occupational Health Insurance Fund. The sample size was determined based on an anticipated effect size of Cohen's d=0.25, based on previous literature (30), representing the minimal clinically relevant change in mental health conditions, and a significance level of 0.05. This calculation ensures the study is appropriately powered to detect meaningful changes in anxiety and depression symptoms (see supplementary material for detailed computations). For a more stringent scenario ($\alpha = 0.001$), we estimated that enrolling 600 participants in two cohorts would provide sufficient sensitivity to detect changes, balancing statistical power and resource constraints.

General population participants will be recruited through a panel survey company, while participants on sick leave will be enrolled by clinical psychologists affiliated with the Occupational Health Insurance Fund. The Scientific Committee of the Occupational Health Insurance Fund will be responsible for selecting and enrolling the clinical psychologists involved in the study. Informed consent will be obtained from all participants before any data collection. See OSF supplementary material for sample size calculation and informed consent details: https://osf.io/u42ma/?view_only=4fa71ed4a4d244c2892ee348e75659c0.

Interventions

The MetrikaMind platform will be presented to the participants on the sick-leave group by clinical psychologists of the Occupational Health Fund Insurance. The platform provides real-time, personalized mental health monitoring and includes:

- **Psychometric assessments:** Regular evaluations of anxiety, depression, and workplace well-being.
- **AI-driven tools:** Predictive models analyzing response patterns to provide personalized recommendations for future mental health management.
- **Response bias detection:** Tools to identify faking (good or bad) in responses, enhancing the accuracy and reliability of assessments.

Adherence to the MetrikaMind platform will be tracked by monitoring the percentage of completed questionnaires available on the app. If a participant fails to complete a questionnaire, they will receive a reminder via text the following day. These messages are intended to promote participant retention and completion of follow-up. Interventions for participants on sick leave will be discontinued under two conditions: 1) upon their discharge or 2) after six months of participation in the study. No adverse or harmful effects related to psychometric assessments are known. Thus, no risks are anticipated for the participants involved on the MetrikaMind Project. and no ancillary and post-trial care are anticipated. Yet, participants in this study are covered by the insurance of IRB 00003099.

Materials

The MetrikaMind project employs a comprehensive set of psychometric tools designed to assess mental health, personality, work engagement, and emotional well-being in workplace environments. The selection of these tools for both baseline and follow-up assessments is based on several guiding principles: the tools assess key constructs, are freely available, exhibit strong psychometric properties, and are validated in both English and Spanish to ensure cross-cultural applicability. Additionally, we prioritized concise scales to minimize participant burden without compromising the quality of data collected. Table 1 shows the key instruments used in this study.

Table 1. Overview of Psychological and Work-Related Assessment Tools Used in the MetrikaMind Project[1]

Acronym	Full Name	Authors	Description
CESD-R	Center for Epidemiologic Studies Depression Scale-Revised	Bergenfeld, 2023 (34)	Assesses depressive symptoms in the general population.
PHQ-9	Patient Health Questionnaire-9	Kroenke, Spitzer, Williams, 2001 (35)	Measures the severity of depression symptoms.
GAD-7	Generalized Anxiety Disorder-7	Spitzer et al., 2006 (36)	Screens for generalized anxiety disorder.
Zung SAS	Zung Self-Rating Anxiety Scale	Zung, 1971 (37)	Assesses anxiety severity with a focus on psychological and somatic symptoms.
PROMIS	Patient-Reported Outcomes Measurement Information System Depression	Pilkonis et al. (2011) (38)	Evaluates depressive symptoms, including negative mood and emotional distress

[1] See https://clinicaltrials.gov/study/NCT06650176 for a detailed description of the outcomes and their metrics

Acronym	Full Name	Authors	Description
DASS-21	Depression, Anxiety, and Stress Scale-21	Lovibond & Lovibond, 1995 (39)	Measures depression, anxiety, and stress.
BFI-2-XS	Big Five Inventory-2 Extra Short Form	Soto & John, 2017 (40)	Assesses five broad personality traits.
H-H	HEXACO Honesty-Humility Scale	Ashton & Lee, 2009 (41)	Assesses honesty, fairness, and modesty.
UWES	Utrecht Work Engagement Scale	Schaufeli & Bakker, 2003 (42)	Measures employee engagement in terms of vigor, dedication, and absorption.
POSS	Perceived Occupational Stress Scale	Marcatto et al., 2022 (43)	Assesses perceived stress in occupational settings.
10Q-FRP	Facilitation, Reinforcement, and Perceived Job Demands	Custom, based on work engagement	Assesses job demands, reinforcement, and facilitation in the work environment.

Besides the Ecological Momentary Assessments (EMA), and to complement the collection of self-reported data, we will also gather information for the AI models through participant activities within the app, as well as passive data collected from sensors. This includes data such as mobility patterns, physical activity, and mobile usage, which will provide additional context and insights into participants' mental health status. These multiple data streams will enhance the platform's ability to generate comprehensive assessments while ensuring strict adherence to privacy regulations to protect participants' rights.

Timeline

Data collection will be conducted separately for the general population and sick leave population. For the **general population**, assessments will be cross-sectional, completed once by participants, and will evaluate anxiety, depression, and social desirability using a nationally representative sample. This allows for accurate prevalence estimates.

For the **sick leave population**, data will be collected from two cohorts of 300 participants each, recruited over two distinct periods. Participants will undergo weekly assessments for up to 6 months or until they return to work. This will track changes in mental health symptoms over time, providing longitudinal data. The staggered recruitment of the two cohorts will ensure comprehensive data collection and facilitate comparisons between groups.

Primary Outcome:

Changes in depression and anxiety symptoms will be tracked using validated psychometric tools, such as the PHQ-9 for depression and the GAD-7 for anxiety. These assessments will be conducted weekly for up to 6 months to evaluate the platform's effectiveness in monitoring symptom evolution over time.

Secondary Outcomes:

- **Personality and Work Engagement:** Personality traits will be assessed using the BFI-2-XS, while the HEXACO H-H scale will measure honesty and integrity. Employee engagement will be evaluated using the UWES, and workplace stress will be assessed via the POSS. The 10Q-FRP will measure job-related factors such as organizational support and job demands.

- **Platform Engagement:** Platform usage data, including the frequency of assessments, adherence, and user feedback, will be analyzed to determine the feasibility and acceptability of the platform.
- **Validation of Predictive Models:** The study will explore the utility of bifactor models in predicting mental health outcomes, focusing on depression and anxiety, based on psychometric data and professional recommendations.

Data management

Data will be stored in the cloud of the University of Barcelona. No personal identifying information will be collected. Each participant will be assigned a unique code, and while sociodemographic data will be gathered, it will not be sufficient to identify individuals, ensuring full compliance with data protection regulations. The personal data collected will be used solely for managing and executing the research project "METRIKAMIND - Development of a Digital Mental Health Ecosystem for Workplace Environments" as part of a mission carried out in the public interest (Spanish Organic Law 2/2023, March 22, of the University System). The recipients of the personal data will be the university itself, specifically the research team for the project, and, if applicable, any data processors. No data will be shared with third parties unless legally required. Any further information related to data collection and management can be found here: https://clinicaltrials.gov/study/NCT06650176#study-overview

A *Data Monitoring Committee* (DMC) is not necessary for the MetrikaMind project for several reasons. First, the study does not involve high-risk interventions or invasive procedures, as it focuses on psychological assessments and digital monitoring, which carry minimal risk to participants. Second, the project uses a pre-post design without a control group, which reduces the need for external monitoring of comparative treatments. Third, the data collected are not critical for the immediate safety of participants, unlike in clinical trials involving new drugs or surgical interventions. Additionally, the study duration is relatively short and does not pose significant potential harm to participants. Finally, participant safety will already be overseen by institutional ethics committees, reducing the need for a separate DMC.

Psychometric methods

In psychometrics, two key measurement models exist (44): causal indicators (formerly called formative indicators) and effect indicators (previously reflective indicators). The MetrikaMind project employs an effect indicator model to assess mental health conditions like anxiety and depression.

A **causal indicator model** suggests that observed symptoms cause the latent mental health construct, aligning with the DSM approach, where diagnoses emerge from sets of symptoms defining the disorder (33). For example, depression is viewed as resulting from symptoms like fatigue or loss of interest, meaning the removal or addition of symptoms changes the disorder. In contrast, an **effect indicator model** assumes that the latent construct drives the observed symptoms. This model, exemplified by the HiTOP framework (45), views symptoms as reflections of broader latent dimensions such as internalizing or externalizing disorders, offering a more nuanced understanding of mental health by focusing on underlying traits (44).

By using the effect indicator model, MetrikaMind focuses on latent traits that drive symptomatology, reducing measurement error and enhancing reliability (46,47). This approach is particularly important for the bifactor analysis used in the study, which is described in the

Statistical Analysis section. By adopting an effect indicator approach, the MetrikaMind project ensures stable and reliable mental health assessments across diverse workplace settings.

Statistical Analysis

Here, the statistical analysis centers on using a bifactor model to improve the reliability and accuracy of assessing anxiety and depression in workplace environments (48). This model helps separate response tendencies—like presenting oneself in a socially desirable way—from genuine mental health symptoms. By doing so, the bifactor model provides a more precise evaluation of anxiety and depression, ensuring that the mental health indicators we measure, called Key Psychological Indicators (KPIs), reflect real psychological states rather than general biases or tendencies to "fake good" or "fake bad" in self-reports (49).

This is particularly relevant in workplace settings where employees may face pressure to underreport symptoms to appear more resilient or healthy. For instance, when employees complete self-assessments, their responses may be influenced by social desirability or a need to conform to perceived workplace norms. In some cases, however, these distortions may not be unconscious; instead, they may involve voluntary distortions, such as impression management or "faking good," where individuals consciously modify their responses to create a favorable impression or to avoid potential negative consequences associated with mental health disclosures (49).

This approach is valuable in public health, where accurate mental health assessments can lead to better-targeted interventions. Research in public health has shown that bifactor models are particularly useful for identifying the specific factors that influence mental health, while controlling for general response biases. For example, bifactor models have been used in public health studies to assess mental health across various populations, helping tailor mental health care to specific needs (50), although their adoption has been somewhat limited in broader public health applications. One reason for this is that bifactor models are computationally complex and require a high level of statistical expertise, which may have limited their widespread use in mental health assessments (51,52).

By leveraging this model, MetrikaMind aims to establish a robust framework for evaluating mental health in the workplace, ensuring that organizations can rely on accurate data when making decisions to support employee well-being.

Model Fitting:

The bifactor model will be fit using confirmatory factor analysis (CFA) in software like Mplus or R (53,54). Model fit will be evaluated using indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA), with acceptable thresholds being CFI and TLI > 0.90 and RMSEA < 0.08 (55). The number of Key Psychological Indicators (KPIs), representing subcomponents of anxiety and depression, will be determined based on both empirical criteria and existing research evidence. To ensure the model's stability across different subgroups, Differential Item Functioning (DIF) analysis will be conducted, assessing whether items perform differently across groups such as gender, age, or job role (56). This will help ensure that both the general factor (e.g., social desirability) and specific factors (e.g., anxiety and depression) remain unbiased.

Missing data will be handled using **multiple imputation** to preserve statistical power and reduce bias, with **sensitivity analyses** conducted to confirm that imputation does not alter the results significantly.

Interpretation of Results:

These data will be used to create **mitigated norms**, which account for response biases identified by the bifactor model. These norms will enhance the accuracy of assessments, ensuring sensitivity to both general workforce members and those on sick leave, whose mental health profiles may differ.

Artificial Intelligence Methods

Artificial Intelligence is a key element in this project. Machine learning offers distinct advantages in enhancing our understanding of psychological constructs and improving measurement accuracy. These techniques can capture complex, non-linear relationships in data that conventional models may overlook, enabling more precise predictions in cases where psychological processes are complex or not fully understood.

Building on this potential, we will go beyond traditional statistical methods to leverage advanced machine learning algorithms for extracting insights directly from psychometric data. Our approach combines the power of predictive models with the need for explainable AI (XAI) in healthcare settings (57,58). This combination allows us to harness the predictive strength of machine learning while maintaining the transparency and interpretability crucial for applications in mental health care:

- Predictive modeling: We will employ classical Machine learning algorithms such as Random Forests (RF) (59) and more recent deep learning Multi-Layer Perceptrons (MLPs) (60) to forecast patient outcomes. In this use case, this would mean predicting the different indicators and alerts for the monitoring system

- Temporal analysis: Once sufficient longitudinal data is available, we will conduct trajectory analysis using sequential modelling techniques, such as deep learning Recurrent Neural Networks (RNNs) (61) to model patient trajectories. This will provide the alerts system with more robust predictive outcomes.
- Interpretability: To maintain transparency, we will use SHAP (62), which show the ranked and weighted list of characteristics that better explains Machine learning model predictions, ensuring healthcare professionals can understand the rationale behind them.

These methods will be integrated into an alert system designed specifically to aid healthcare professionals. The system will use as inputs psychometric data from patients in this study, along with previous assessments by mental health professionals, as training data. By analyzing this information, the system will predict key patient outcomes related to psychological constructs, including the severity of the condition, estimated recovery time, and recommended interventions. It will do so taking into account subtle changes detected by the refined psychometric tools. Alerts will be classified by concerns such as honesty, responsibility, stagnation in progress, worsening symptoms, and readiness for discharge, with each alert detailing management time and priority. This approach enables us to extract meaningful insights from each prediction, deepening our understanding of patient needs and improving resource allocation.

Upon deployment of the data-driven alert system on MetrikaMind's platform, we will enable real-time tracking of patients and outcomes. The timely alerts will help the mental health professionals, suggesting interventions when possibly necessary at the earliest convenience. As a result, human resources can be allocated more efficiently, prioritizing assistance for the most urgent cases.

Furthermore, the alert system is designed for continuous improvement. By progressively incorporating more patient data, the model can be adapted to further enhance its predictive accuracy. This iterative process not only improves the system's performance but also reveals valuable population-level correlations related to mental health outcomes. These insights can inform broader strategies for prevention and intervention.

Discussion

The MetrikaMind project presents an innovative approach to workplace mental health, utilizing digital tools, psychometrics, and AI to provide real-time assessments and predictive algorithms. The goal is to bridge current gaps in mental health solutions, offering more accurate and timely assessments for anxiety and depression. This study contributes to the growing evidence of the effectiveness of digital mental health platforms, particularly in addressing the demand for scalable interventions (63,64).

One of the strengths of the project is its focus on addressing response biases like social desirability through bifactor models. These models help separate genuine symptoms from social pressures or intentional manipulation, providing a clearer understanding of mental health in the workplace (65). Additionally, the study introduces mitigated norms for mental health assessments, improving accuracy across different workplace environments by accounting for potential biases in self-reported data.

The project aims to provide economic and organizational benefits by reducing anxiety and depression in the workforce, which are known to reduce productivity and increase absenteeism and presenteeism (66). By offering data-driven interventions, the platform has the potential to enhance employee well-being, reduce costs, and improve organizational performance (29).

However, the project has several limitations. The one-arm, pre-post design, while suitable for developing bifactor models, lacks the control of randomized controlled trials (RCTs), limiting causal conclusions about the platform's effectiveness (67). To address this, future projects are planned for primary care applications (68).

Another limitation is the reliance on self-reported data, which is prone to underreporting or overreporting symptoms. Although the bifactor model helps mitigate response biases, it may not fully eliminate them, particularly in workplace environments where employees feel pressure to present themselves favorably (69). To address this, the study plans to incorporate alternative data sources, such as passive data from mobile and physical activity, to provide a more comprehensive assessment (70).

The sample population may also limit generalizability, as the sick leave participants are drawn from a specific entity (Occupational Health Insurance Fund) and may not represent all employees on sick leave or in other regions. This restricts the applicability of the mitigated norms beyond the study context. However, we believe that the findings of this project can ultimately impact all other areas in which mental health is relevant, such as primary care settings.

Finally, the platform's weekly assessments for participants on sick leave may introduce participant fatigue, potentially leading to dropout or incomplete data (71). To mitigate this, the study plans to use Item Response Theory (IRT) to develop shorter versions of the questionnaires, maintaining psychometric rigor while reducing participant burden (31).

Additionally, the longitudinal nature of the data collection may pose challenges in participant retention, particularly if participants return to work before completing the study (72).

Conclusions

The MetrikaMind project addresses the need for scalable mental health solutions in the workplace by utilizing advanced psychometric assessments, AI-driven algorithms, and real-time data analysis, focusing on anxiety and depression. It is poised to deliver substantial social, economic, and scientific benefits in workplace mental health. Economically, addressing anxiety and depression in the workplace is expected to enhance productivity, lower absenteeism, and mitigate presenteeism, translating into substantial cost savings for employers. The platform is expected to contribute to the field of digital mental health by providing accurate assessments and enhancing workplace interventions through both active and passive data sources. With its emphasis on real-time assessments and precise monitoring, the platform has the potential to improve both employee well-being and organizational performance. It offers valuable insights into the connection between mental health and workplace productivity, while supporting future development of more effective interventions.

List of abbreviations

10Q-FRP	Facilitation, Reinforcement, and Perceived Job Demands
BFI-2-XS	Big Five Inventory-2 Extra Short Form
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index

DASS-21	Depression, Anxiety, and Stress Scale-21
DIF	Differential Item Functioning
DMC	Data Monitoring Committee
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
EMA	Ecological Momentary Assessments
GDPR	General Data Protection Regulation
GAD-7	Generalized Anxiety Disorder-7
H-H	HEXACO Honesty-Humility Scale
HiTOP	Hierarchical Taxonomy of Psychopathology
IRT	Item Response Theory
IRB	Institutional Review Board
KPIs	Key Psychological Indicators
MLPs	Multi-Layer Perceptrons
PHQ-9	Patient Health Questionnaire-9
POSS	Perceived Occupational Stress Scale
PROMIS	Patient-Reported Outcomes Measurement Information System Depression
RF	Random Forests
RMSEA	Root Mean Square Error of Approximation
RNNs	Recurrent Neural Networks
SHAP	Shapley Additive Explanations
TLI	Tucker-Lewis Index

TRIPOD	Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis
UWES	Utrecht Work Engagement Scale
XAI	Explainable Artificial Intelligence
Zung SAS	Zung Self-Rating Anxiety Scale

Declarations

Ethical Considerations

This study will adhere to the principles outlined in the **Declaration of Helsinki** and the **Oviedo Convention**, which emphasizes the protection of human rights in biomedical research. Informed consent will be obtained from all participants, who will be fully informed about the study's objectives, procedures, risks, and their right to withdraw at any time. Participant confidentiality will be maintained, and data will be anonymized and securely stored in accordance with **GDPR** guidelines.

This protocol has been reviewed and approved by the **Institutional Review Board (IRB 00003099)**, ensuring compliance with all ethical and regulatory requirements. Any significant amendments to this protocol would be subjected to re-registration on https://clinicaltrials.gov/study/NCT06650176#study-overview

Availability of data and materials

This manuscript does not contain any data. However, all questionnaires, the study protocol, materials, and scripts (except for those protected by intellectual property) will be made available in an Open Science Framework (OSF) repository upon publication. The repository link is: https://osf.io/u42ma/?view_only=4fa71ed4a4d244c2892ee348e75659c0.

Dissemination policy

Trial results will be shared with the public and relevant stakeholders through scientific publications, conferences, and workshops.

Competing interests

DG-P is the scientific director of Metrika Mind Health, S.L., and although he does not currently receive funds from the company, he has received funding in the past. SE is a scientific advisor of Metrika Mind Health and currently receives funds from the company. All other authors (AT, BD-A, and GM) declare that they have no competing interests.

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Authors' contributions

DG-P conceptualized the study and the design and wrote the manuscript. AT, BD-A, GM, AC, and SE contributed to the writing and reviewing of the manuscript. All authors have read and approved the final version of the manuscript.

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