***Review Article***

**Dashboards: A Data-Driven Framework for Organisational Decision-Making and Employee Well-Being Building Mental Health Index**

**Abstract**

Due to rising mental health issues in the workplace, organizations need to take preemptive, data-driven measures to foster employee well-being. In this review article, a complete, data-driven framework for constructing Mental Health Index Dashboards specific to organizational environments is introduced. Desk review was employed. Credible journals and reliable online materials were used and findings were presented thematically. Through the integration of quantitative and qualitative data sources such as employee surveys, productivity metrics, absenteeism records, and sentiment analysis, the proposed framework is able to produce real-time and actionable insights. Using visualization of data and machine learning, the dashboard allows human resource professionals and decision-makers to track changes in mental health over time, identify high-risk groups and assess changes in the effectiveness of interventions over time. The review presents the study of ethical data handling, employee privacy and transparency of the organization; and presents best practices for such implementation. Case studies and deployment of prototype dashboards show how such dashboards can create a healthier workplace, reallocate resources, and find long-term mental health strategies.

**Keywords:** Mental Health Index, Data-Driven, Decision Making, Employee Well-Being, Dashboard, Predictive Analytics

**1.0 INTRODUCTION**

People’s well-being encompasses good mental health. Mental health is good when people can cope with the normal stresses of life; realize their capabilities; feel good about themselves and work productively (World Health Organization, 2019). On the other hand, according to Rehm and Shield (2019), and OECD (2021), one of the largest and fastest-growing categories of the burden of disease worldwide is mental ill-health, with its economic costs, including investment in the mental health system and foregone employment and productivity, accounting for more than four per cent of GDP in OECD countries.

In the fast-paced and competitive business atmosphere, organizations comprehend more and more the benefit of data utilization for becoming better decision-makers. Human Resource Analytics is a section of workforce analytics which systematically examines worker data to enhance business practices (Garcia and Adams, 2022). By combining multiple data sources (employee performance metrics, engagement surveys, demographic information), companies can derive actionable insights that can inform talent management strategies. Workforce analytics is important because it can take raw data and convert it into useful information that can help steer strategic initiatives for increasing employee productivity and well-being (Okon et al., 2024). There are rising pressures on organizations to get the most out of their human capital investments. An era characterized by fast-moving technology, talent and emerging dynamics is realizing that the conventional methods of managing talent are no longer enough (Ma, 2023). This shortcoming requires a shift to data-driven methodologies, that can enable decision-making, and employee engagement & optimize overall organizational efficiency.

A usual habit for many is to either see a doctor or discuss how they feel with friends and family when they are ill. Talking about or treating mental illnesses happens less often than with physical problems. The Mental Health Million Project (Newson et al., 2021) reported that only around 45% of people in the United States with serious mental health problems receive professional help. The negative attitudes and expensive costs of care prevent many people from discussing or getting needed care for their mental health problems (Coombs et al., 2021).

Many websites that use healthcare data for visualization use just one source of information or concentrate on illnesses like cancer and heart disease (CDC-GIS, 2018). These more extensive websites meant for mental health usually involve a complicated layout or ask only limited questions, not offering a general picture of mental health issues (Mental Health America, 2022; MHTTC, 2022). At present, there is no simple web tool that shows public data about the frequency and unequal treatment of common mental illness symptoms. In many situations, such an app could help people with mental illness and those who support them feel linked to others, while also allowing public health officials and epidemiologists to see the widespread nature of mental illness.

Even though the role of mental health at work is gaining notice, companies find it hard to systematically follow, assess and enhance employee mental health due to separate data sources, no uniform set of measures and little connection with decision-making. There is an urgent requirement to build a detailed mental health index dashboard that organizes important mental health data, supplies useful insights and helps with decisions that promote employee well-being and efficient mental health programs in organizations. The study is directed at learning about how a dashboard can be made, put into action and used effectively to enhance workplace outcomes and encourage proactive mental health in the office (Ballard et al., 2025). The application of data analytics has changed the way organizations handle employee well-being. Organizations can make data-driven decisions to improve the degree of employee satisfaction, productivity and efficiency of the organization as a whole.

Mental health is increasingly recognized as a fundamental component of public health. Mental health index dashboards have emerged as a need for reliable and timely mental health outcomes data that is available to guide and inform decision-making. These dashboards are designed as interactive data-driven platforms to monitor trends in mental health, to help evaluate service delivery and to aid in policy-making and advocacy efforts. In this review, the structure, functionality, examples, benefits and challenges of mental health index dashboards, were explored.

**2.0 LITERATURE REVIEW**

**2.1 Employee Productivity and Well-Being**

Employee productivity is entwined with employee well-being and both of these concepts matter greatly for organizational performance. There are many things that can influence an employee’s ability to do their best such as from individual traits to the culture of an organization. Several key drivers of employee productivity, i.e., motivation, job satisfaction, work-life balance, and leadership were identified in research by Van De Voorde et al., (2012). Employee productivity is hinged on motivation. Employees who are intrinsically motivated are more engaged and more committed to their work which means higher levels of productivity. Intrinsic motivation includes factors regarding, recognition, opportunity for growth and meaningful work. On the other hand, extrinsic motivators like money or promotions can boost productivity (Iwe et al., 2023; Oluokun et al., 2023a) — especially if the incentives (or lack thereof) reflect what people value. Another important variable impacting the productivity of an employee is job satisfaction.

A study indicates that workers are more productive and do not leave the company as often. Some of the things that make people happy in their jobs are a comfortable workplace, management that supports and paths for career growth. Firms that focus on employee happiness tend to build a work environment where people engage and come together, resulting in better productivity (Elumilade et al., 2022). Being able to balance work and personal life has become very important these days. Having a balance between thriving professionally and personally usually leads to higher job satisfaction and better overall health. Having work flex time or the ability to work from home can both improve work-life balance and boost productivity.

According to Ajiga et al. (2024), organizations that understand the need for work-life balance and support the same through suitable sections of rules are in default to pull in and reel in leading ability. Leadership is very much essential in moulding the level of productivity and well-being of employees. High performers work for leaders who show emotional intelligence, give constructive feedback and encourage transparent communication. Studies indicate that transformational leadership styles, that encourage and stimulate employees, are connected to elevated employee engagement and productivity. Organizations which invest in leadership development programs can foster effective leaders that lead to positive change in employee performance (Haddad et al., 2018). Though individual factors affect a worker’s productivity, organizational culture matters a lot as well. Employee well-being, collaboration and continuous improvement are valued and an environment is created where employees will thrive.

Mental health-supporting organizations that provide easy access to wellness resources and are building a culture of support make the productivity of employees possible and improve the overall well-being of employees (Bristol-Alagbariya et al., 2024; Oluokun et al., 2024b). Finally, the interrelationship between productivity and well-being is also complicated. Also, research shows that if you are constantly reaching very high productivity levels and you’re not managing it properly, you are going to get stressed out and you are going to burn out. However, companies that invest in initiatives like mental health support and various stress management programs in the workplace and even work-life integration, can lower the probability of burnout and be more productive. For organizations interested in achieving sustainable performance outcomes, the interplay between quality, time, cost and resources (or the construct of the critical elements consisting of these four constructs) needs to be recognized (Chintoh et al., 2024).

**2.2 Mental Health and Employee Well-being**

Recently, more people have become aware of how important mental health is. Because more people are affected by mental disorders worldwide (Cénat et al., 2021), those responsible for care and treatment are actively working on new ways to support them. Starting to use data-led mental health systems that rely on machine learning is an approach that is improving and being adopted by more countries (Narayanrao & Kumari, 2020). They seek to use a large amount of information from different places, including electronic health records, wearables and what patients record themselves (Aggarwal & Girdhar, 2022; An et al., 2022).

Machine learning models are key to finding hidden trends that can go unnoticed by healthcare practitioners in a data-driven mental healthcare system (Nayan et al., 2022). Many models from machine learning such as supervised learning, unsupervised learning and deep learning, have been put to use for studying mental health data. For example, models for supervised learning (Saha et al., 2023) learn from data that has been labelled, so they can predict outcomes like the probability a person relapses or the success of a given intervention. Unsupervised learning (Krishnan et al., 2020) helps find hidden information in data by not using predefined labels and therefore brings out new ideas.

When it comes to mental health, psychologists often use electronic health records (Taquet et al., 2021), genetic data, brain scans and activity on social media sites. Because machine learning handles so many different sources of data, it provides healthcare providers with a full overview of a patient’s mental health. When we extract features from data, we might include details about a person’s background, health history, habits and actions which provide insight into mental health (Liu et al., 2022).

One benefit of data-driven mental health systems is that they can give customized care, especially during pandemics (Arivoli et al., 2022). Machine learning is impressive in mental health because it can adapt its interventions to fit each person’s needs. With the help of detailed data analysis, machine learning can design personalized intervention plans that are tailored to each patient’s details which in return boosts the accuracy of mental health treatments (Mukhiya et al., 2022).

In data-driven systems, machine learning starts by gathering data and then extracting the dataset (Gandhi & Mishra, 2022). After that, the algorithms work on many tasks such as data preprocessing, including filtering, managing missing information, reducing noise, tokenization, vectorization, editing, showing data, and making final reports. When machine learning and data-driven methods are combined in this manner, there is a powerful potential to enhance mental health care, considering the recent trends in mental health applications (Alrizq et al., 2022).

For this reason, data-driven systems and machine learning predictions are closely linked, as they both play a key role in every data-based decision-support system (Thieme et al., 2020; Khumprom & Yodo, 2019). Data in these systems is classified into structured, unstructured and semi-structured categories (Siriyasatien et al., 2018) and afterwards, it is processed and analyzed. Apart from gathering data from conventional sources such as Facebook and Twitter, data available from questionnaires, studies by cohort and direct interviews owe their existence to passive sensing (Alharbi & Fkih, 2022). People not only share information on social media but also allow their phones to share data constantly. Multisided data such as spatial information, sensor readings, graphs and activity logs (Burkom et al., 2021) help a lot during machine learning training. Realizing how essential passive sensing is in data collection matters, given it enhances our understanding of different causes in the variety of data used for decision-making in mental health.

User-friendly access to data data-driven system allows to integration of multiple data sources, means to use data in application form and reporting of the results in various conceptual terms. The reliability of data-driven decision-making is the most important reason for the need for data-driven systems. The stages which comprise the data-driven decision-making framework include data collection, organization, analysis, summarization, synthesis and prioritization (Yu et al., 2021). Due to this, data and ML models will continue to be a part of the healthcare domain driving the transformation process and hence will remain dependent on a set of dependable and adaptive machine learning data-driven architecture frameworks (Aldabbas et al., 2022). As data is collected from different sources using multiple channels in different formats, designing an interoperable framework in a way such that the flow of the process is smooth and secure is required before actually aggregating data in ensemble models. The importance of reusability, automated machine learning prediction and human decision support (AI) has been emphasized, taking into account (Alreshidi & Ahmad, 2019) the feature of explainability of these decision support systems, thus providing human experts with the ability to navigate and interpret the decision-making process (Terhorst et al., 2023).

**2.3 Empirical Review: Related Works**

The study carried out by Kaur, Sharma & Mittal (2018) investigated big data analytics in the healthcare domain leading to the creation of four major pillars – patient-centric care, incorporating health records, drug history, patient behaviour and preferences, real-time patient monitoring via wearable sensors, disease prediction and also enhancing the treatment method. In this study, the healthcare architecture was developed with four layers: Data source, Storage, security and machine learning-based application layer, whereby more emphasis was placed on security and privacy.

Likewise, Patel & Gandhi (2018) worked on big data analytics in the area of health care, by employing ensemble models. The review shows the evident advantages of using big data analytics with machine learning despite the challenges of managing big data such as different data structures, data storage, management, integration and processing.

This work contributes to a study conducted by Khan et al. (2022) in which they covered comprehensive and systematic research on the healthcare domain using data analytics to analyze disease diagnosis in that area within articles published from 2011 to 2021. Such findings indicate that the implementation of cloud computing applications and hybrid machine learning–based models for advanced decision might be of great advantage in the healthcare sector, given its experience in applying large amounts of data and extensive knowledge. The advantages of these are cost reduction in treatments, the decrease in simulation time and it leads to a higher quality of care. These technologies are positive and policymakers can push researchers and practitioners to develop more advanced disease-diagnosing models by encouraging the adoption of these technologies which will thereby increase the overall quality of patient treatment. It was also found that architectures for cognitive computing using hybrid machine learning would be useful tools to aid in the data-driven analysis of health care big data and that the results hold great promise for future applications. Several findings are based on the background study.

**2.4 Leveraging Technology for Tailored Well-being Programs**

Because of digital change, many companies now rely on technology to improve and customize their employee well-being programs (Selimović et al., 2021, Trenerry, et. al., 2021). This study explores ways in which technology supports the design of personal wellness programs and examines the use of wellness apps, insights from data and inventive ideas for helping people of different categories. Organizations use technology to personalize and create well-being programs specifically designed for their employees. Using wellness applications and platforms can now help people have personalized health experiences. The applications support different areas of health for employees, for example, exercise, diet, mindfulness and good sleep. Because employees can use these tools on their own time, they are free to shape their well-being course. You can often set goals, follow your achievements and interact with the app which encourages people to manage their health more actively.

Further, the incorporation of wearables, (fitness trackers and smartwatches), boosts the personalization of well-being programs. Torrey Wailer, Medical Director of Zocdoc Enhanced Care, says these devices offer real-time data on physical activity, sleep patterns and other health metrics which employees and employers can track and monitor trends in wellbeing.

Data analytics has a key role in tailoring well-being programs for employees by getting important data about employee health and preferences. Organizations can tweak and tweak their initiative based on the rates of participation data, program effectiveness and user feedback. Insights such as these allow HR professionals to understand trends, spot unique needs of employee segments and make more data-driven decisions on improving program relevance. Predictive analytics are also used to determine when possible, well-being challenges are likely to arise and allow them to design proactively possible interventions. With data, organisations are able to adapt their strategies to tackle particular well-being problems or lifestyle styles, shifting to a more particular and impactful manner to enhance the well-being of individuals (Jeske, 2022; Parker & Grote, 2022).

In addition, companies are testing new technologies to help people learn to relax, for example by using virtual reality (VR) for meditation and mindfulness exercises. A newer way of providing mental health support is through these immersive experiences, suitable for the needs of a technology-savvy workforce (Babapour et al., 2021; Wontorczyk & Rożnowski, 2022).

Using technology to customise well-being programs in organizations is a different paradigm of caring for employees in organizations (Elufioye et al., 2024). Wellness applications, data analytics and innovative technologies are integrated in such a way that organizations can no longer settle for one-size-fits-all and can now embrace personalized, data-driven well-being. In the evolving workplace, technology will be the key to successful well-being programs that are inclusive, adaptable and impactful — to meet the changing and varied needs of the modern workforce. With technology at their disposal, organizations can develop a culture of well-being that connects with individuals in diverse groups to make it easier to find work that increases positivity and well-being for everyone (Elufioye et al., 2024).

**3.0 METHODOLOGY**

This review employs a desk review. A qualitative synthesis is utilized in this desk review which explores existing literature, frameworks and case studies on the development of Mental Health Index Dashboards as data-informed decision-making/platform for employees’ well-being within an organization. The methodology included searching peer-reviewed journals, institutional reports and trustworthy online materials between 2015 and 2025. In this vein, key databases such as PubMed, Scopus, ScienceDirect, Google Scholar and some institutional websites such as the World Health Organization (WHO), the Mental Health at Work Index academic repositories arXiv, and JMIR, were used. Keywords such as “mental health dashboard”, “Employee wellbeing”, “data-driven HR” and “workplace mental health analytics” were the search terms. Finally, selection criteria centred on relevance, methodological rigour, and recency, so that the review is based only on high-quality and applicable resources.

Documents were thematically analyzed to determine common components of mental health dashboards, data sources and types, outcomes for the organization and ethical considerations after sourcing.

**4.0 RESULTS AND DISCUSSIONS**

**4.1 Psychological Well-Being Metrics in the Built Environment**

The demand for user-centred environments for psychological well-being is amongst others increasing in the context of the built environment (Watson, 2018). An innovative operational definition for accounting for building users’ well-being outcomes and impact reporting through Social Return on Investment (SROI) is presented, consisting of a multi-item scale to measure and quantify the well-being outcomes experienced by building users and tools for impact reporting that produce transferable and monetized evaluation metrics. As a combination, this has the potential to give people the tools to communicate the value of design both powerfully and accessibly and represent an opportunity to develop new user-driven knowledge and shape the built environment in positive ways.AI and Big Data in Mental Healthcare (Watson, 2018).

**4.2 Artificial Intelligence (AI) and Big Data Technologies**

Artificial intelligence and big data technologies applied to mental health have the potential to personalize treatment selection, prognosticate, monitor for relapse, detect early in (and help prevent) mental health disorders before they reach clinical symptom thresholds and even deliver some care. (Rosenfeld et al., 2019). There are, of course, several unique challenges encountered in incorporating mental health applications, including a lack of widely used or validated biomarkers, and reliance on questionnaire data from patients and clinicians. These pose barriers regarding the implementation of these technologies. Despite this, AI and big data show the potential to enhance mental healthcare through personalization and proactiveness (Rosenfeld et al., 2019).

**4.3 People Analytics Effectiveness Framework**

With the concept of the “People Analytics Effectiveness Wheel,” Peeters, et al. (2020) introduce and highlight four important categories for people analytics to work: enabling resources, products, stakeholder management and governance structure. It offers a complete view of the necessary components for organizations to implement people analytics and create value for the organization’s performance.

**4.4 Employee Well-Being and Organisational Effectiveness**

Through the study conducted by Hejase et al. (2024) in Lebanon, the relationship between employee well-being and organizational effectiveness was explored. Factors (such as flexibility, work-life balance, and psychological well-being), are found to be positively correlated with organizational outcomes (including retention, quality of work and productivity) of the organization. The need to integrate employee well-being into organizational decision processes therefore comes to light.

**4.5 AI-Driven Human Resource Decision-Making**

Artificial intelligence (AI) is integrated into human resource management (HRM) and these decision-making processes are being reshaped. According to Taslim et al. (2025) however, the themes which systematically emerged from a review of AI-driven HRM are: AI adoption, AI ethics, AI-driven human resource decision-making, and AI performance. The research further underscores the key role of employee involvement in AI-driven HR decision-making as a key facilitator for acceptance and operational success.

**4.6 Common Mental Health Issues in the Workplace**

**Depression**: A mental health disease known also for depression is a prevalent mood disorder which is defined by feelings of helplessness, depression, and loss of interest or pleasure in habits. It prevents employees from concentrating and doing daily tasks and results in strained relations; in some cases, it comes with physical symptoms like a change in appetite and disturbed sleep. Depression also affects work performance and all-round quality of life (Medbury Medicals, 2023).

**Stress and Burnout**: Heavy workloads, long hours and tight deadlines also impose too much pressure on a worker’s mental health. A person would be prone to burnout if prolonged stress leads to emotional exhaustion, decreased productivity and physical health problems like hypertension (Medbury Medicals, 2023; Chellappa, 2024). Burnout has been identified as a serious work phenomenon related to employee well-being.

**Anxiety Disorders**: There are common anxiety disorders, for example, in workplaces, we innervate Generalized Anxiety Disorder (GAD), Panic Disorder, and Social Anxiety Disorder. There are disorders in which people are beset with anxiety disorders, panic attacks and a generalized fear of being judged by others in their social life which in turn prevent them from properly performing their work and their participation in social work (Szuhany & Simon, 2022; Medbury Medicals, 2023). It can strain workplace relationships and reduce team productivity as well.

**Bipolar Disorder**: Bipolar has mood swings that include manic as well as depressive episodes which can cause employees to waver in focus, decision-making and interpersonal communication. These manic episodes can result in impulsive behaviour, irritability and a negative impact on the harmony and productivity of the workplace (Medbury Medicals, 2023).

**Schizophrenia**: While less common, schizophrenia is an extremely serious mental illness in which the individual experiences hallucinations and delusions that greatly hinder concentration and interaction with others which also hinder workplace function (Medbury Medicals, 2023).

**Post-Traumatic Stress Disorder (PTSD)**: Trauma can cause PTSD among employees and the effects can negatively impact their mental health, presenting as symptoms like flashbacks, anxiety, and avoidance behaviours which affect work performance (Yehuda et al., 2015).

**4.7 Descriptions of Examples of Mental Health Index Dashboards**

**U.S. Mental Health Dashboard**

This is an R Shiny-developed interactive web application which allows exploratory data analysis of U.S. mental health data from national surveys. It consists of visualizations of prevalence and geo-distribution of mental health metrics to raise awareness and reduce stigma (Arvelo & Plantinga, 2023).

**Mental Health in Canada Dashboard**

This dashboard features indicators related to different dimensions of mental health (positive mental health, mental disorder, mental health care and suicide) hosted by the Public Health Agency of Canada. Users can explore data by topic and by demographic factors (Public Health Agency of Canada, 2024).

**Digital Dashboard for Mental Health in Nairobi, Kenya**

This open-source dashboard was implemented to summarise mental, neurological and substance use disorder data in real-time in Nairobi, Kenya. Data capture and reporting were improved hence valuable information for planning and advocacy (Mwanga et al. 2024).

**4.8 Framework: A Data-Driven Framework for Organisational Decision-Making and Employee Well-Being**

Building a mental health index dashboard presents a comprehensive approach to leveraging data for enhancing mental health outcomes within organizations. The framework emphasizes the integration of diverse data sources and systematic measurement to support decision-making that promotes employee well-being and organizational performance.

**Key Strengths of the Framework**

**Interdisciplinary Development:** The framework is fashioned by a cadre of experts drawn from organizational, clinical and occupational health psychology, public health and management system fields to provide a comprehensive and evidence-based approach to addressing the siloed nature of attention to workforce mental health research and practice (Ballard et al., 2025).

**Comprehensive Measurement and Monitoring:** It says we need to have a comprehensive system to measure, monitor and report on mental health metrics. It covers Baseline needs assessments, process and outcome evaluations and continuous improvement mechanisms. Data-driven practices can help organizations know which mental health risks to identify, have to set priorities, know, what programs work and make good decisions to optimize mental health interventions (Ballard et al., 2025).

**Organizational-Level Practices Focus**: The framework highlights a variety of organizational policies and behaviours that should be used to support workforce mental health (for instance, flexible work arrangements, employee assistance programs, leadership support, diversity, and inclusion). The systemic perspective is consistent with evidence that the workplace environment and culture have a significant influence on mental health outcomes (Ballard et al., 2025).

**Privacy and Ethical Considerations:** It points out that data collection for mental health should be private and confidential to follow ethics and gain the trust of employees (Ballard et al., 2025).

**Alignment with Broader Mental Health Objectives:** The framework fits with broader intentions in mental health, as it focuses on psychiatric illness, well-being, recovery, reducing stigma and caring for physical health, much like is present in national mental health dashboards and indices (Williams, 2018; European Public Health Alliance [EPHA], 2025).

The framework gives organizations a helpful resource to support employee well-being by making decisions with better data. The organized practice of interdisciplinary skills, comprehensive tracking and suitable policies leads to better workforce well-being and follows changing public health priorities.

**4.9 Building Mental Health Index Dashboards**

Building mental health index dashboards for organizational decision-making and employee well-being implies bringing together pertinent mental health indicators, data sources and visualization tools for delivering actionable insights that make sense for designing workplace mental health strategies.

**Key Components of Mental Health Index Dashboards**

Multiple Data Sources & Indicators: An effective dashboard will rely on a variety of data sources including demographic surveys, employment rates (unemployment and disability), health insurance coverage and routine health checkups to create a multi-sided mental health index. For example, the Healthy Cities Index can track component indicators relevant to community mental health through data sources such as the American Community Survey and CDC PLACES. In the same way, data on the mental health burden, policies and system strength is also aggregated at the global level for various national-level decision-making (UNICEF, 2023).

**Organizational Metrics**: For workplace-focused dashboards, it is essential to measure metrics that directly or indirectly reflect including mental health and organizational impact e.g. short and long-term disability claims, employee engagement, benefits utilization, and absenteeism. Over 90 KPIs per Bell Canada’s mental health scorecard measure the progress and ROI of mental health programs (Jensen, 2020). These metrics help identify problem areas early and support targeted interventions.

**Dashboard Features:** Interactive dashboards should be able to provide exploration dashboards providing interactive exploration such as filtering demographics, time and geography and with a variety of visualization techniques including heat maps, radar charts and proportional symbol maps for identifying patterns and trends (GitHub, 2023). It thus enables organizations to track the risk of mental health in various employee groups and monitor their interventions.

**Data Collection and Reporting:** The relevance of insights greatly increases as data is collected at the most granular level possible (teams or departments). For example, follow-up and detailed reporting are recommended by systems such as DHIS2 if one were to choose to assign datasets to the lowest organisational units. Direct and indirect mental health questions in employee surveys are supplemented by administrative data to get a fuller picture (City Mental Health Alliance, 2015).

**4.10 Benefits for Organizational Decision-Making and Employee Well-Being**

**Dashboards:** Mental health dashboards consolidate mental health data to inform leaders to identify risks, and enable better allocation of resources and custom policies to meet employees’ needs (Memish et al., 2017).

**Early Identification and Intervention:** Organizations should monitor key indicators note early emerging signs of mental health issues and respond proactively in order to improve employee’s well-being and productivity (City Mental Health Alliance, 2015).

**Accountability:** Regular reporting enhances accountability to stakeholders and helps to monitor the progress aligned to the mental health goals (Memish et al., 2017).

**Customization to Organizational Context:** The metrics chosen should be consistent with the organizational context in terms of culture and decision-making because it ensures the data is actionable and relevant (Jensen, 2020).

**4.11 Examples of Mental Health Index Dashboards**

Below are a few examples of mental health index dashboards that serve to help you make better decisions within your organization as well as help your employees maintain better well—being.

**4.11.1 Canada Federal Public Service Workplace Mental Health Dashboard**

A Power BI-driven dashboard that presents psychosocial risk factors contextual to the National Standard of Canada for Psychological Health and Safety in the Workplace.

It creates scores for 11 of the 13 psychosocial factors based on Public Service Employee Survey data from several years (2019, 2020 and 2022).

Analysis can be run at multiple organizational levels (from enterprise-wide to subunits) and can be filtered on demographics and time to identify strengths and gaps in psychological health and safety.

The tool is intended to assist organizations in being able to systematically measure and improve workplace mental health and to assess progress over time (Federal Public Service, Canada, 2024).

**4.11.2 UK NHS England Mental Health Dashboards**

Mental health dashboards: NHS Digital’s suite of interactive Power BI dashboards looks at service activity, Mental Health Act usage, restrictive interventions, autism waiting times and population mental health surveys.

Data were available on these dashboards at more than one geographic level or organisational level, for example, national, regional, local authority, and provider.

Stakeholders are able to enhance their awareness of trends, demographic breakdowns and service performance to help inform policy and, importantly, inform operational decisions in the spheres of mental health care and well-being (NHS England 2024).

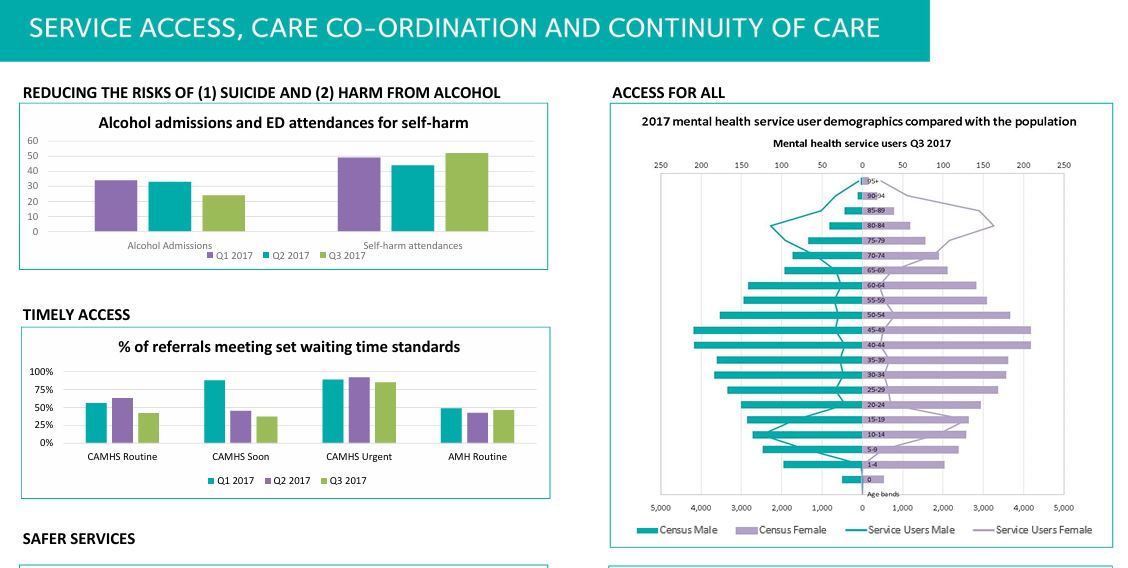
**4.11.3 Psychological Health and Safety Dashboard (New Zealand Resource)**

This tool shows a psychological health and safety dashboard, located in New Zealand; it helps identify areas for improvement and includes an audit to guide its implementation.

It’s a resource for offering example dashboards and data sources as resources for reporting psychosocial risks in the workplace.

It is designed to assist organizations in recognizing data that is relevant to them and to visualize relevant indicators to monitor the psychological health and safety of workers for mental health initiatives (New Zealand Government, 2024).

**Pictorial Example of Mental Health Index Dashboards**



**Figure 1:** *Example of Mental Health Index Dashboards (Source Mental Health Quality Report 2017: Third Quarter)*

**4.12 Key Barriers in Current Mental Health Dashboards**

While these dashboards are important for decision-making and employees’ welfare, they have flaws that hold them back from being fully useful. Addressing these problems can boost what they can achieve and help them play a bigger role.

**Some Dashboards Miss Out on Coverage:** For example, the Federal Public Service’s Workplace Mental Health Dashboard focuses only on 10-11 of 13 psychosocial risk factors and does not take into consideration all of the recent important mental health standards (Federal Public Service, Canada, 2024).

Many dashboards mainly depend on surveys that are not optimized to test all important psychosocial or mental health risks. This can reduce how correct and thorough the data is (Federal Public Service, Canada, 2024).

Data on employee views on mental health stigma, confidentiality matters and their willingness to get help is not captured by many dashboards, even though these barriers impact many people (Dewa & Hoch, 2015; Singh, 2024).

Mental Health Dashboards often fail to deal with major barriers to mental health care, including not realizing one has a problem, various beliefs and difficulties accessing support because of the system. These issues have a significant effect on how well workplace mental health programs work (Dewa & Hoch, 2015).

**It Does Not Have Real Time or Frequent Data Updates:** Many dashboards contain updated information that is not often and continues to be (annually or biannually) which could cause a delay in identifying the emerging mental health issues or its effect on the implemented interventions.

**Current Dashboards:** While some dashboards track absenteeism or disability claims, there are fewer dashboards with measures of productivity and performance that include measures of presenteeism, productivity loss or measures of cognitive impacts such as difficulties in concentration (Sigh, 2024).

**Dashboards Currently Not Granularly Customized for Diverse Workforces:** This is because dashboards are deficient in showing granular demographic breakdowns and not enabling the ability to deduce insights from various employee groups on which knowledge is crucial as different populations face divergent mental health risks (HumAngle, 2024).

**4.13 Improving Mental Health Index Dashboards**

All relevant psychosocial factors should be included to create a more complete picture of workplace mental health risks (WHO, 2024; WHO & ILO, 2024) which would specifically include discrimination, workload, job control and work-life balance.

**Incorporation of Stigma and Confidentiality Metrics:** Measures that account for employee belief about mental health, perceived stigma and belief and trust in confidentiality need to be included to further understand barriers to reaching support (Dewa & Hoch, 2015; Singh, 2024).

**Tracking Barriers to Care:** Combine measures of recognition of mental health needs, attitudinal impediments and systemic impediments to care use to identify specific points to make to enhance treatment use (Dewa & Hoch, 2015).

**Timely or more often Than Real-Time Data Collection:** Use digital tools and pulse surveys to collect more frequent data for immediate /faster response and ongoing monitoring.

**Metrics to integrate Productivity and Cognitive Function Metrics**: Presenteeism, focus, ability to make decisions, focus and fatigue are included to correlate mental health status with performance on the organizational level (Dewa & Hoch, 2015).

Filter and analyze by age, gender, job role, location and other demographics to effectively create strategies on mental health targeted to a special group of people (HumAngle, 2024).

**Quantitative Data and Employee Feedback or Qualitative Data:** Use qualitative data available from employee feedback, focus groups or open-ended survey responses in addition to the quantitative data.

**Actionable Insights and Recommendations:** Additionally, dashboards should include Actionable Insights and Recommendations to plug the gap identified – actions that need to be taken in light of the identified gaps for example, in resource allocation, where policies need to be adjusted, etc.

**Confidentiality and Data Privacy Assurance:** Communicating how employee data is protected will contribute to the development of confidence which will in turn result in participation in mental health assessments (Dewa & Hoch, 2015**).**

**4.14 Key Challenges Associated with the Creation of Mental Health Index Dashboards**

There are a number of challenges facing the creation of mental health index dashboards for organizational decision-making and employee well-being.

**Data Collection and Quality Issues**: Accurate, comprehensive and timely mental health data is hard to collect. Many of the organizations currently rely on employee surveys which may not fully reflect psychosocial risks or mental health status and the data is updated infrequently, preventing real-time insights. In addition, privacy concerns may decrease employee’s willingness to share sensitive information which could affect the completeness and reliability of the data (Paterson et al., 2024; Pearson, 2024).

**Stigma and Confidentiality Concerns**: The biggest barrier to honest reporting and engagement in mental health initiatives remains mental health stigma. For instance, employees may be afraid of any possible form of discrimination or breach of confidentiality, thus underreporting symptoms or refusing to participate in assessments as these will lower the accuracy of the dashboard (Quinane et al., 2021; Paterson et al., 2024).

**Resource Constraints:** There is a limited budget, time and personnel to mount comprehensive mental health measurement and intervention programs. Nevertheless, the majority of Wellbeing Leads are unable to secure adequate resources to cultivate and maintain highly sophisticated dashboards and associated endeavours, even with leadership support (Quinane et al., 2021; Pearson, 2024).

**Integration with Organizational Context and Systems**: Organizational policies, workflows and culture present the difficulty in the alignment of mental health dashboards. Such dashboards may be underutilized or unutilized because they do not fit properly into the organization or are not engaging leadership and managers to effectively use them (Paterson et al., 2024).

**Sector and Workforce Diversity**: Each faces challenges to mental health and implementation barriers which are different per each industry and workforce segment (SMEs, Healthcare, Construction, ICT). In order for dashboards to be meaningful and actionable they must be adaptable to sector-specific contexts and be sensitive to demographic diversity (Paterson et al., 2024).

**Measuring Impact and Outcomes**: The linkage of mental health data to business outcomes such as productivity, absenteeism and employee engagement, is very complex. Dashboards will likely not provide value to decision-makers and will not garner investment and support without clear metrics and analytic capabilities, (Pearson, 2024).

**Technical and Analytical Challenges**: For a user to have a pleasant experience, appropriate technical makeup and technical sophistication are needed. Therefore, organizations sometimes lack the in-house capability to design, update and interpret any complex mental health indices (Pearson, 2024).

**5.0 CONCLUSION AND RECOMMENDATIONS**

**5.1 Conclusion**

Modern public health management relies on mental health index dashboards. They change raw information into details that guide health advocacy, the preparation of resources and decisions on policies. Challenges also exist, but improved data technology and infrastructure will help them have an even bigger impact.

**5.2 Key Recommendations**

For an efficient Mental Health Index Dashboard to be constructed that enables effective organizational decision-making and improving the health state of the employees, we need to conceptualize well-defined, multi-dimensional metrics. Mental health is a complicated issue and cannot be reduced to a single score or key indicator. A dashboard of employee mental health should relate to at least multiple dimensions, namely stress levels, work-life balance, sleep quality, risk of burnout, employees’ engagement, perceived social support, and so on.

As the dashboard’s design and deployment are concerned, transparency, anonymity and ethical data practices must be prioritized. Employee trust is key because mental health data is very sensitive and in order to be good data, employees need to be accurate and easy to participate. It’s critical that data is collected, anonymized, stored and used in the proper way and organizations need to communicate how this is done. Individual privacy needs to be protected such that only team-level insights should be reported.

There is a need to be able to integrate real-time and long-term data together to derive useful insights. However, a one-time snapshot of mental health does not provide much value. Regular pulse surveys—monthly or quarterly—are instead a better way to monitor (issues should be compatible with the length of time between surveys) and longitudinal analysis provides a way to identify patterns and to anticipate issues before they get out of control.

***Ethical Standards***

There is compliance with ethical standards. The review does not involve contact with humans.

**References**

Aggarwal, R., & Girdhar, N. (2022, May). Machine learning role in cognitive mental health analysis amid Covid-19 crisis: a critical study. In *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON)* (Vol. 1, pp. 90-96). IEEE.

Ajiga, D. I., Adeleye, R. A., Tubokirifuruar, T. S., Bello, B. G., Ndubuisi, N. L., Asuzu, O. F., & Owolabi, O. R. (2024). Machine learning for stock market forecasting: a review of models and accuracy. *Finance & Accounting Research Journal*, *6*(2), 112-124.

Aldabbas H., Albashish D., Khatatneh K., & Amin, R. (2022). An architecture of IoT-aware healthcare smart system by leveraging machine learning*. International Arab Journal of Information Technology, 19*(2), 160–172. DOI 10.34028/iajit.

Alharbi, T. S., & Fkih, F. (2022). Building and testing fine-grained dataset of COVID-19 tweets for worry prediction. *International Journal of Advanced Computer Science and Applications*, *13*(8).

Alreshidi, A., & Ahmad, A. (2019). Architecting software for the internet of thing based systems. *Future Internet*, *11*(7), 153.

Alrizq, M., Solangi, S. A., Alghamdi, A., Nizamani, M. A., Memon, M. A., & Hamdi, M. (2022). An Architecture Supporting Intelligent Mobile Healthcare Using Human-Computer Interaction HCI Principles. *Comput. Syst. Sci. Eng.*, *40*(2), 557-569.

An, J. E., Kim, K. H., Park, S. J., Seo, S. E., Kim, J., Ha, S., ... & Kwon, O. S. (2022). Wearable cortisol aptasensor for simple and rapid real-time monitoring. *ACS sensors*, *7*(1), 99-108.

Arivoli, A., Golwala, D., & Reddy, R. (2022). CoviExpert: COVID-19 detection from chest X-ray using CNN. *Measurement: Sensors*, *23*, 100392.

Arvelo, I., & Plantinga, A. (2023). US Mental health dashboard. *The New England Journal of Statistics in Data Science*, *2*(3), 323-329.

Babapour Chafi, M., Hultberg, A., & Bozic Yams, N. (2021). Post-pandemic office work: Perceived challenges and opportunities for a sustainable work environment*. Sustainability, 14*(1), 294.

Ballard, D. W., Lodge, G. C., & Pike, K. M. (2025). Mental health at work: a practical framework for employers. *Frontiers in Public Health*, *13*, 1552981.

Bristol-Alagbariya, B., Ayanponle, L. O., & Ogedengbe, D. E. (2024). Sustainable business expansion: HR strategies and frameworks for supporting growth and stability. *International Journal of Management & Entrepreneurship Research*, *6*(12), 3871-3882.

Burkom, H., Loschen, W., Wojcik, R., Holtry, R., Punjabi, M., Siwek, M., & Lewis, S. (2021). Electronic Surveillance System for the Early Notification of Community-Based Epidemics (ESSENCE): overview, components, and public health applications. *JMIR public health and surveillance*, *7*(6), e26303.

Canada Federal Public Service (2024*). User Guide: Federal Public Service Workplace Mental Health Dashboard.* <https://www.ute-sei.org/sites/default/files/2024-11/User%20Guide%20-%20Mental%20Health%20Dashboard.pdf>

CDC-GIS Centers for Disease Control and Prevention (2018). Online Public Health Maps. https://www.cdc.gov/gis/ public-health-maps.htm.

Cénat, J. M., Dalexis, R. D., Guerrier, M., Noorishad, P. G., Derivois, D., Bukaka, J., ... & Rousseau, C. (2021). Frequency and correlates of anxiety symptoms during the COVID-19 pandemic in low-and middle-income countries: a multinational study. *Journal of psychiatric research*, *132*, 13-17.

Chellappa, S. (2024). *Mental health in the workplace: Challenges and solutions*. <https://engagedly.com/blog/mental-health-in-the-workplace-challenges-solutions/>

Chintoh, G. A., Segun-Falade, O. D., Odionu, C. S., & Ekeh, A. H. (2024). International Journal of Social Science Exceptional Research.

City Mental Health Alliance (2015). What is good mental health in the city workplace and how do we measure it? *Frontier Economics,* Public Health England. https://mhfaengland.org/mhfa-centre/news/measuring-city-mh/cmha-fe-summary-report-pdf-15-03-15.pdf

Coombs, N. C., Meriwether, W. E., Caringi, J., & Newcomer, S. R. (2021). Barriers to healthcare access among US adults with mental health challenges: A population-based study. *SSM-population health*, *15*, 100847.

Dewa, C. S., & Hoch, J. S. (2015). Barriers to mental health service use among workers with depression and work productivity. *Journal of occupational and environmental medicine*, *57*(7), 726-731.

Elufioye, O. A., Ndubuisi, N. L., Daraojimba, R. E., Awonuga, K. F., Ayanponle, L. O., & Asuzu, O. F. (2024). Reviewing employee well-being and mental health initiatives in contemporary HR Practices. *International Journal of Science and Research Archive*, *11*(1), 828-840.

Elumilade, O. O., Ogundeji, I. A., Achumie, G. O., Omokhoa, H. E., & Omowole, B. M. (2022). Optimizing corporate tax strategies and transfer pricing policies to improve financial efficiency and compliance. *Journal of Advance Multidisciplinary Research*, *1*(2), 28-38.

European Public Health Alliance (2025). *Building Better Indicators for Mental Health and Wellbeing.* <https://epha.org/wp-content/uploads/2025/05/building-better-indicators-for-mental-health-and-wellbeing-report.pdf>

Gandhi, N., & Mishra, S. (2022). Explainable AI for healthcare: a study for interpreting diabetes prediction. In *Machine Learning and Big Data Analytics (Proceedings of International Conference on Machine Learning and Big Data Analytics (ICMLBDA) 2021)* (pp. 95-105). Springer International Publishing.

Garcia, A., & Adams, J. (2022). Data-Driven decision making: leveraging analytics and AI for strategic advantage. *Research Studies of Business*, *1*(02), 77-85.

GitHub (2023). *Mental Cares: Tracking Mental Health in the United States.* <https://github.com/leiyunin/mental-health-dashboard>

Haddad, S., Badran, O., & Daood, A. (2018). The impact of transformational leadership style on employees’ job satisfaction. *International Journal of Pure and Applied Mathematics*, *119*(18), 887-900.

Hejase, H. J., El Dirani, A., Haidar, Z., Alawieh, L., Ahmad, A. A., & Sfeir, N. (2024). The Impact of Employee Well-Being on Organizational Effectiveness: Context of Lebanon. *International Journal of Human Resource Studies*, *14*(2), 15-54.

HumAngle (2024). *Understanding the Mental Health of Nigerian Workers.* <https://humanglemedia.com/understanding-the-mental-health-of-nigerian-workers/>

Iwe, K. A., Daramola, G. O., Isong, D. E., Agho, M. O., & Ezeh, M. O. (2023). Real-time monitoring and risk management in geothermal energy production: ensuring safe and efficient operations.

Jensen, S. (2020). *Measuring employee wellness during COVID-19: What business leaders need to know*. <https://www.tableau.com/blog/measuring-employee-wellness-during-covid-19-what-business-leaders-need-know>

Jeske, D. (2022). Remote workers' experiences with electronic monitoring during Covid-19: implications and recommendations. *International Journal of Workplace Health Management, 15*(3), 393-409.

Kaur, P., Sharma, M., & Mittal, M. (2018). Big data and machine learning based secure healthcare framework. *Procedia computer science*, *132*, 1049-1059.

Khan, S., Khan, H. U., & Nazir, S. (2022). Systematic analysis of healthcare big data analytics for efficient care and disease diagnosing. *Scientific Reports*, *12*(1), 22377.

Khumprom, P., & Yodo, N. (2019). A data-driven predictive prognostic model for lithium-ion batteries based on a deep learning algorithm. *Energies*, *12*(4), 660.

Krishnan, J., Purohit, H., & Rangwala, H. (2020). Unsupervised and interpretable domain adaptation to rapidly filter tweets for emergency services. In *2020 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM)* (pp. 409-416). IEEE.

Liu, Y., Xie, Y. N., Li, W. G., He, X., He, H. G., Chen, L. B., & Shen, Q. (2022). A machine learning-based risk prediction model for post-traumatic stress disorder during the COVID-19 pandemic. *Medicina*, *58*(12), 1704.

Ma, W. (2023). Exploring the transformation effects of digitalization on traditional human resources management. *Polish Journal of Management Studies*, *28*.

Medbury Medicals. (2023, July 1). *Common mental health issues encountered in the workplace*. <https://medburymedicals.com/common-mental-health-issues-encountered-in-the-workplace/>

Memish, K., Martin, A., Bartlett, L., Dawkins, S., & Sanderson, K. (2017). Workplace mental health: An international review of guidelines. *Preventive medicine*, *101*, 213-222.

Mental Health America (2022). County and State Data Map: Defining Mental Health Across Communities. Accessed: 2022-09 29.

MHTTC (2022). Southeast MHTTC Data Visualization Resources Accessed: 2022-09-27.

Mukhiya, S. K., Lamo, Y., & Rabbi, F. (2022). A reference architecture for data-driven and adaptive internet-delivered psychological treatment systems: Software architecture development and validation study. *JMIR Human Factors*, *9*(2), e31029.

Mwanga, D. M., Waruingi, S., Manolova, G., Wekesah, F. M., Kadengye, D. T., Otieno, P. O., ... & EPInA Study Team. (2024). A digital dashboard for reporting mental, neurological and substance use disorders in Nairobi, Kenya: Implementing an open source data technology for improving data capture. *PLOS Digital Health*, *3*(11), e0000646.

Narayanrao, P. V., & Kumari, P. L. S. (2020). Analysis of machine learning algorithms for predicting depression. In *2020 international conference on computer science, engineering and applications (iccsea)* (pp. 1-4). IEEE.

Nayan, M. I. H., Uddin, M. S. G., Hossain, M. I., Alam, M. M., Zinnia, M. A., Haq, I., ... & Methun, M. I. H. (2022). Comparison of the performance of machine learning-based algorithms for predicting depression and anxiety among University Students in Bangladesh: A result of the first wave of the COVID-19 pandemic. *Asian Journal of Social Health and Behavior*, *5*(2), 75-84.

New Zealand Government (2024). *Data sources and dashboard for psychological health and safety.* Government Health and Safety Lead. <https://www.healthandsafety.govt.nz/a-z-topics/mentally-healthy>work/resources/data-sources-for-psychological-health-and-safety/

Newson, J., Sukhoi, O., Taylor, J., Topalo, O. & Thiagarajan, T. (2021). Mental State of the World 2021. Technical Report, Sapien Labs.

NHS England (2024). *NHS mental health dashboard*. <https://www.england.nhs.uk/mental-health/taskforce/imp/mh-dashboard/>

OECD Publishing. (2021). *A New Benchmark for Mental Health Systems: Tackling the Social and Economic Costs of Mental Ill-Health*. Organisation for Economic Co-operation and Development OECD.

Okon, R., Odionu, C. S., & Bristol-Alagbariya, B. (2024). Integrating data-driven analytics into human resource management to improve decision-making and organizational effectiveness. *IRE Journals*, *8*(6), 574.

Oluokun, O. A., Akinsooto, O., Ogundipe, O. B., & Ikemba, S. (2024a). Optimizing Demand Side Management (DSM) in industrial sectors: A policy-driven approach.

Oluokun, O. A., Akinsooto, O., Ogundipe, O. B., & Ikemba, S. (2024b). Leveraging Cloud Computing and Big Data analytics for policy-driven energy optimization in smart cities.

Parker, S. K., & Grote, G. (2022). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology, 71*(4), 1171-1204.

Patel, H. B., & Gandhi, S. (2018, May). A review on big data analytics in healthcare using machine learning approaches. In *2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 84-90). IEEE.

Paterson, C., Leduc, C., Maxwell, M., Aust, B., Strachan, H., O’Connor, A., ... & Greiner, B. A. (2024). Barriers and facilitators to implementing workplace interventions to promote mental health: qualitative evidence synthesis. *Systematic reviews*, *13*(1), 152.

Pearson, E. (2024). *The Four Biggest Challenges for Wellbeing Leads in Implementing Mental Health and Wellbeing Strategies.* Wellbeing Lead Academy. https://wellbeingleadacademy.uk/insights/mental-health/the-four-biggest-challenges-for-wellbeing-leads-in-implementing-mental-health-and-wellbeing-strategies

Peeters, T., Paauwe, J., & Van De Voorde, K. (2020). People analytics effectiveness: developing a framework. *Journal of organizational effectiveness: people and performance*, *7*(2), 203-219.

Public Health Agency of Canada. (2024, June 20). *Mental health in Canada dashboard: Indicator index*. Government of Canada. https://health-infobase.canada.ca/mental-health/indicators/

Quinane, E., Bardoel, E. A., & Pervan, S. (2021). CEOs, leaders and managing mental health: a tension-centered approach. *The International Journal of Human Resource Management*, *32*(15), 3157-3189.

Rehm, J., & Shield, K. D. (2019). Global burden of disease and the impact of mental and addictive disorders. *Current psychiatry reports*, *21*, 1-7.

Rosenfeld, A., Benrimoh, D., Armstrong, C., Mirchi, N., Langlois-Therrien, T., Rollins, C., Tanguay-Sela, M., Mehltretter, J., Fratila, R., Israel, S., Snook, E., Perlman, K., Kleinerman, A., Saab, B., Thoburn, M., Gabbay, C., & Yaniv-Rosenfeld, A. (2019). Big data analytics and AI in mental healthcare. *arXiv*. <https://arxiv.org/abs/1903.12071>

Saha, S., Dutta, S., Goswami, B., & Nandi, D. (2023). ADU-Net: an attention dense U-Net based deep supervised DNN for automated lesion segmentation of COVID-19 from chest CT images. *Biomedical Signal Processing and Control*, *85*, 104974.

Selimović, J., Pilav-Velić, A., & Krndžija, L. (2021). Digital workplace transformation in the financial service sector: Investigating the relationship between employees' expectations and intentions. *Technology in Society*, *66*, 101640.

Singh, S. S. (2024). Mental Health in the Workplace: Challenges and Solutions. *Int J Recent Sci Res.15*(10), 5035-5042.

Siriyasatien, P., Chadsuthi, S., Jampachaisri, K., & Kesorn, K. (2018). Dengue epidemics prediction: a survey of the state-of-the-art based on data science processes. *IEEE Access*, *6*, 53757-53795.

Szuhany, K. L., & Simon, N. M. (2022). Anxiety disorders: a review. *Jama*, *328*(24), 2431-2445.

Taquet, M., Geddes, J. R., Husain, M., Luciano, S., & Harrison, P. J. (2021). 6-month neurological and psychiatric outcomes in 236 379 survivors of COVID-19: a retrospective cohort study using electronic health records. *The Lancet Psychiatry*, *8*(5), 416-427.

Taslim, W. S., Rosnani, T., & Fauzan, R. (2025). Employee involvement in AI-driven HR decision-making: A systematic review. *SA Journal of Human Resource Management*, *23*, 1-10.

Terhorst, Y., Knauer, J., & Baumeister, H. (2022). Smart sensing enhanced diagnostic expert systems. In *Digital phenotyping and Mobile sensing: New developments in Psycho informatics* (pp. 413-425). Cham: Springer International Publishing.

Thieme, A., Belgrave, D., & Doherty, G. (2020). Machine learning in mental health: A systematic review of the HCI literature to support the development of effective and implementable ML systems. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *27*(5), 1-53.

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y., & Oh, P. H. (2021). Preparing workplaces for digital transformation: An integrative review and framework of multi-level factors. *Frontiers in psychology,* 822.

UNICEF (2023). *Countdown for Global Mental Health 2030 Dashboard.* https://data.unicef.org/resources/countdown-for-global-mental-health-2030-dashboard/

Van De Voorde, K., Paauwe, J., & Van Veldhoven, M. (2012). Employee well‐being and the HRM–organizational performance relationship: a review of quantitative studies. *International Journal of Management Reviews*, *14*(4), 391-407.

Watson, K. J. (2018). Establishing psychological wellbeing metrics for the built environment. *Building Services Engineering Research and Technology*, *39*(2), 232-243.

WHO & ILO (2024). *Mental health at work: Policy Brief*. https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@ed\_protect/@protrav/@safework/documents/publication/wcms\_856976.pdf

Williams, D. J. (2018). No health without ‘mental health’. *Journal of Public Health*, *40*(2), 444-444.

Wontorczyk, A., & Rożnowski, B. (2022). Remote, hybrid, and on-site work during the SARS-CoV-2 pandemic and the consequences for stress and work engagement. *International journal of environmental research and public health, 19*(4), 2400.

World Health Organization (2019). Mental health, https://www.who.int/news-room/facts-in pictures/detail/mental-health (accessed on 16 May 2022).

World Health Organization (2024). *Mental health at work*. <https://www.who.int/news-room/fact-sheets/detail/mental-health-at-work>

Yehuda, R., Hoge, C. W., McFarlane, A. C., Vermetten, E., Lanius, R. A., Nievergelt, C. M., ... & Hyman, S. E. (2015). Post-traumatic stress disorder. *Nature reviews Disease primers*, *1*(1), 1-22.

Yu, S., Qing, Q., Zhang, C., Shehzad, A., Oatley, G., & Xia, F. (2021). Data-driven decision-making in COVID-19 response: A survey. *IEEE Transactions on Computational Social Systems*, *8*(4), 1016-1029.