***Review Article***

**A Data-Driven Dashboard Framework for Employee Mental Health and Organisational Decision-Making**

**Abstract**

Due to rising mental health issues in the workplace, organisations 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 organisational environments is introduced. This paper utilised a desk review approach. This involves a comprehensive review of scholarly journals. 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. Findings show that 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 further presents the study of ethical data handling, employee privacy, and transparency of the organisation, 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.

Essentially, the dashboard framework creates an enabling atmosphere in which mental health is emphasised and discussed. At the same time, it enhances the productivity of employees, as possible cases of stress are identified at an early stage, each employee is given personalised assistance, and resources are distributed based on data. The framework triggers greater engagement, more employees who are less subject to burnout, and a healthier, more resilient workforce through enforcing mental health in the strategy decision-making process. The review recommends that longitudinal impact studies can be considered to examine the effect of the framework on employees’ well-being and organisational decision-making in the long run.

**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 Organisation, 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, organisations comprehend more and more the benefit of data utilisation 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 organisations to get the most out of their human capital investments. An era characterised by fast-moving technology, talent and emerging dynamics is realising 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, employee engagement & optimise overall organisational 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 visualisation 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 organisations. 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 organisations handle employee well-being. Organisations can make data-driven decisions to improve the degree of employee satisfaction, productivity and efficiency of the organisation as a whole.

Mental health is increasingly recognised 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 organisational performance. There are many things that can influence an employee’s ability to do their best, such as individual traits to the culture of an organisation. 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), organisations that understand the need for work-life balance and support the same through suitable sections of rules are in default to pull in and retain leading talent. 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, which encourage and stimulate employees, are connected to elevated employee engagement and productivity. Organisations which invest in leadership development programs can foster effective leaders who lead to positive change in employee performance (Haddad et al., 2018). Though individual factors affect a worker’s productivity, organisational 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 organisations 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 organisations 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 recognised (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 customised 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 personalised intervention plans that are tailored to each patient’s details, which in turn 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, tokenisation, vectorisation, 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 analysed. Apart from gathering data from conventional sources such as Facebook and Twitter, data available from questionnaires, studies by cohort, and direct interviews owes its 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), helps a lot during machine learning training. Realising how essential passive sensing is in data collection matters, given that it enhances our understanding of different causes in the variety of data used for decision-making in mental health.

User-friendly access to data-driven systems allows for the 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, organisation, analysis, summarisation, synthesis and prioritisation (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 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 Mental Workload**

Mental workload is one key aspect that affects the mental health and productivity level of employees. Mental workload is a complex construct which has many definitions. It could be interpreted as how much one has to use their brain every time, or what level of thinking power is being used, how much pressure one has to put through their thinking, or how capable of processing information is someone? Mental workload is also an essential variable in the case of the collaboration between humans and machines. Mental workload imbalances may lead to serious outcomes. An example here is that when the work is too much, one may feel fatigued fast, lose flexibility and their chances of making mistakes increase (Qu et al., 2020). On the other hand, extremely low workload may lead to wastage of resources invested in human beings and worsening of job performance (Qu et al., 2020). The connection between mental illness and mental workload is also complicated, as it happens in both directions. High mental workload, that is, the mental demands and requirements of a task, may lead to stress and strain. Its stress can lead to exacerbated pre-existing mental health or potentially worsen its occurrence of new ones (Fukuura & Shigematsu, 2021).

**2.4 Importance of Monitoring Employee Mental Workload**

Mental workload monitoring of the employees cannot be overestimated. It is important in a few ways. The first one is that it allows the employer to know the cognitive work and resources required in various tasks, so that the demands of the work do not exceed the capacity of an individual. Particularly, this is significant when it comes to the case of employees with mental illnesses, as they might have a higher mental workload because of their problems with concentration, memory, or fatigue (Fukuura & Shigematsu, 2021). Workplaces are in a position to assist their employees' workability and overall mental health by paying special attention to work demands and personal abilities. We also have to monitor the mental workload and find out the imbalance which can cause big effects.

Unusually large tasks may cause rapid weariness, reduced pliability and a greater possibility of committing mistakes. Consequently, in contrast, extremely low workloads may lead to underutilization of human resources and deterioration of job performance. Moreover, effective monitoring and management of mental workload will help employers to minimise the possibility of work-related stress, chronic stress, depression, and burnout and preserve the health of workers, minimise human errors, and maximise the effectiveness of organisations (Lorber & Dobnik, 2022).

**2.5 Empirical Review: Related Works**

The study carried out by Kaur et al. (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.

SLR by Plaza, Diaz & Perez (2018) was devoted to cyber-physical systems, including the incorporation of sensing, computing, and communication into a system aimed at monitoring, control, and interaction with actual processes. The main purpose behind conducting this systematic review was to find effective solutions that can be of great help to the architects and practitioners when making healthcare projects. The search results synthesis created a knowledge base of software architectures of health care cyber-physical systems, including the stakeholders’ interests, functional, and non-functional requirements, quality aspects, and architectural views.

Avci et al. (2020), on the other hand, concentrated on architectures of large-scale data systems and paid detailed attention to diverse aspects, including the domain of applications, architectural views, patterns, concerns, quality traits, design methodologies, technology, and stakeholders. This SLR provided a detailed analysis of big data software designs, such as a survey and comparison of architecture styles in several domains.

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 analyse 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-making 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 healthcare big data, and that the results hold great promise for future applications. Several findings are based on the background study.

A modelling tool in the other article by Mukhiya, Lamo & Rabbi (2022) established a user-profiling model within a reference architecture to accommodate adjustment and customisation of intervention delivery to the individual users. With the help of this proposed reference architecture, an open-source framework of an adaptive intervention design and planning tool was created. The framework was assessed in some mixture of a case study, expert assessment, and software quality metrics. Other issues like adaptability, scalability, reusability and security, interoperability, and modifiability were evaluated. Yet, the assessment was not carried out about other important indicators, such as reliability, data quality, and performance.

There was a survey and a comparison of big data architectures across various domains of application (Macak, Ge & Buhnova, 2020). In this study, the top architectures of each domain were selected to guide the researchers and practitioners in the same field. Moreover, cross-domain comparison was carried out in order to distinguish between similarities and differences in the domain-specific architectures. The paper concluded with the development of practical guidelines to assist big data researchers and practitioners in the formulation and enhancement of their architecture by utilising what is found during this study.

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

Because of digital change, many companies now rely on technology to improve and customise 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. Organisations use technology to personalise and create well-being programs specifically designed for their employees. Using wellness applications and platforms can now help people have personalised 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 personalisation 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 plays a key role in tailoring well-being programs for employees by getting important data about employee health and preferences. Organisations 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 interventions. With data, organisations are able to adapt their strategies to tackle particular well-being problems or lifestyle styles, shifting to a more specific 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 organisations is a different paradigm of caring for employees in organisations (Elufioye et al., 2024). Wellness applications, data analytics and innovative technologies are integrated in such a way that organisations can no longer settle for one-size-fits-all and can now embrace personalised, 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, organisations 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).

**2.7 The Potential of Analytical Dashboards for Decision-Making**

In this current age, the importance of dashboards cannot be ignored. Analytical dashboards are going to transform the process of decision-making, especially in the complicated aspect of software development. Dashboards provide a working mechanism where raw data can be understood in the form of pictures, charts, graphs, and summaries in an attempt to understand trends, patterns, and outliers within a given context. Such visual clarity enables decision-makers to promptly obtain an overview of how overall a project is doing and where attention or correction is needed (Schreiber et al., 2021). As Schreiber et al. (2021) remark, with the help of analytical dashboards, it is possible to get detailed knowledge of different crucial factors during the process of software development. They are capable of providing a general layout of the whole development process, depicting the inter-relationship between the developers and other outsiders, and how the software under development progresses. Dashboards may also be useful in analysing the quality, reliability and trustworthiness of software through provenance or mapping of the development of processes. Such openness enables the responsible selection of decision-making about code issues, testing plans, and possible weaknesses.

Analytical dashboards are able to help managers and stakeholders make informed decisions faster, based on condensed and visually structured data. Monitoring crucial measurables and seeing a perfect schedule of a project development, dashboards provide the opportunity to identify the possible obstacles or lags in the process and react to them before it is too late. The capability to evaluate the effects of changes to the processes and real-time tracking of the progress enables the agile adaptation and constant enhancement of the development lifecycle. A robust way of streamlining the decision-making process and making a complex software project more efficient and successful in general can be achieved through analytical dashboards (Schreiber et al., 2021).

**2.8 Benefits and Challenges of Using Dashboards for Workload Analysis**

Workload analysis is very critical to employees’ mental health and organisational decision-making. Only employees with good mental health can actively participate and contribute meaningfully to business decision-making that will drive the organisation. Dias et al. (2018) provided an interactive analytic dashboard and designed it with the help of a 4-level hierarchy of a process model and cognitive load measures combined with events and situational data on surgical operations. The dynamic dashboard can analyse certain procedures or total data on various operations. It provides measurements that are timestamped by second and allows display of metrics on a team member by team member level, with optional display of cognitive load breakouts on the entire surgery, during stages or tasks. The research presents some of the advantages and disadvantages associated with the use of dashboards in workload analysis.

Studies demonstrate the worth of mental workload dashboards when it comes to combining varied data sources as a way of comprehensively examining cognitive requirements using surgery as an instance (Dias et al., 2018). Interaction between physiological measures, behavioural measures, and the context informs these dashboards with a highly dimensional, multi-modal view of the variables that influence attention demands on complex procedures. Such a comprehensive view is essential in determining the underlying reasons for mental overload and in guiding specific intervention. These dashboards provide real-time visualisation of the metrics of cognitive load, the implications of which are enormous in terms of situational awareness and the management of disturbances in surgical teams (Dias et al., 2018).

Dashboards can reduce the occurrence of disruptive events due to certain individuals on individual team members by clarifying the cognitive states in the team to reduce unplanned events that interfere and create havoc within the team. Cognitive dashboards are also capable of reducing the burdens of cognition in surgery settings. The actual monitoring reveals the instances of heavy mental loads, which are usually related to the raised vulnerability to distractions and making mistakes (Dias et al., 2018). With such an understanding, surgical teams can be in a stronger position to have proactive measures in place against wrongdoing. Also, bringing the measures of mental workload into the clinical decision support systems might provide technology-based alerts and recommendations less intrusive and more adaptive to the changing cognitive load of a team (Dias et al., 2018).

According to the results provided by Rabiei and Almasi (2022), one of the largest groups of challenges of analytical dashboards in hospitals is connected to data quality and integration. Possible errors in data entail manual inaccuracies in data entry and failure to achieve standard data formats. As well, efficient transfer of information across systems and minimised turnaround time is important for the possibility of real-time dashboard insights. Another aspect that requires effective dashboard design, where obstacles appear quite often, is creating the content (Rabiei & Almasi, 2022). Rabiei and Almasi (2022) have conducted a study according to which Dashboards have to address various requirements of different end-users, involving a significant number of stakeholders in the design process. The indicators of the selected performance are required to be in close agreement with the strategic objectives of the company. The need to provide enough information and not to clutter it through excessive pointers is also important.

**3.0 METHODOLOGY**

This paper utilised a desk review approach by examining scholarly journals and materials. In addition, a qualitative synthesis is utilised 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 organisation. 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 Organisation (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.

Collated documents (journals and online materials) were thematically analysed to determine common components of mental health dashboards, data sources and types, outcomes for the organisation 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 monetised 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 play a significant role in mental health. Artificial intelligence and big data technologies applied to mental health have the potential to personalise 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 to the implementation of these technologies. Despite this, AI and big data show the potential to enhance mental healthcare through personalisation and proactiveness (Rosenfeld et al., 2019).

**4.3 People Analytics Effectiveness Framework**

People analytics strongly influence organisational performance, especially in the area of decision making. 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 organisations to implement people analytics and create value for the organisation’s performance.

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

The mental soundness of employees and organisational effectiveness are inseparable. The effectiveness level of any business or company hinges on the well-being of the workers. Through the study conducted by Hejase et al. (2024) in Lebanon, the relationship between employee well-being and organisational effectiveness was explored. Factors (such as flexibility, work-life balance, and psychological well-being) are found to be positively correlated with organisational outcomes (including retention, quality of work and productivity) of the organisation. The need to integrate employee well-being into organisational 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**

This section explores the key mental health issues experienced by employees in their various workplaces. This ranges from depression, stress and burnout, anxiety disorders, bipolar disorders, to schizophrenia.

**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 activities. 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 overall 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 encounter Generalised Anxiety Disorder (GAD), Panic Disorder, and Social Anxiety Disorder. There are disorders in which people are beset with anxiety disorders, panic attacks and a generalised 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 disorder 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 visualisations 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 organisations. The framework emphasizes the integration of diverse data sources and systematic measurement to support decision-making that promotes employee well-being and organisational performance.

**Key Strengths of the Framework**

**Interdisciplinary Development:** The framework is fashioned by a cadre of experts drawn from organisational, 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 organisations know which mental health risks to identify, have to set priorities, know what programs work and make good decisions to optimise mental health interventions (Ballard et al., 2025).

**Organisational-Level Practices Focus**: The framework highlights a variety of organisational 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 organisations 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 organisational decision-making and employee well-being implies bringing together pertinent mental health indicators, data sources and visualisation 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).

**Organisational Metrics**: For workplace-focused dashboards, it is essential to measure metrics that directly or indirectly reflect, including mental health and organisational impact, for example, short and long-term disability claims, employee engagement, benefits utilisation, 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 visualisation techniques including heat maps, radar charts and proportional symbol maps for identifying patterns and trends (GitHub, 2023). It thus enables organisations 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 Organisational 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:** Organisations should monitor key indicators, note early emerging signs of mental health issues, and respond proactively in order to improve employees’ 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).

**Customisation to Organisational Context:** The metrics chosen should be consistent with the organisational 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 organisation 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 organisational 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 organisations 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).

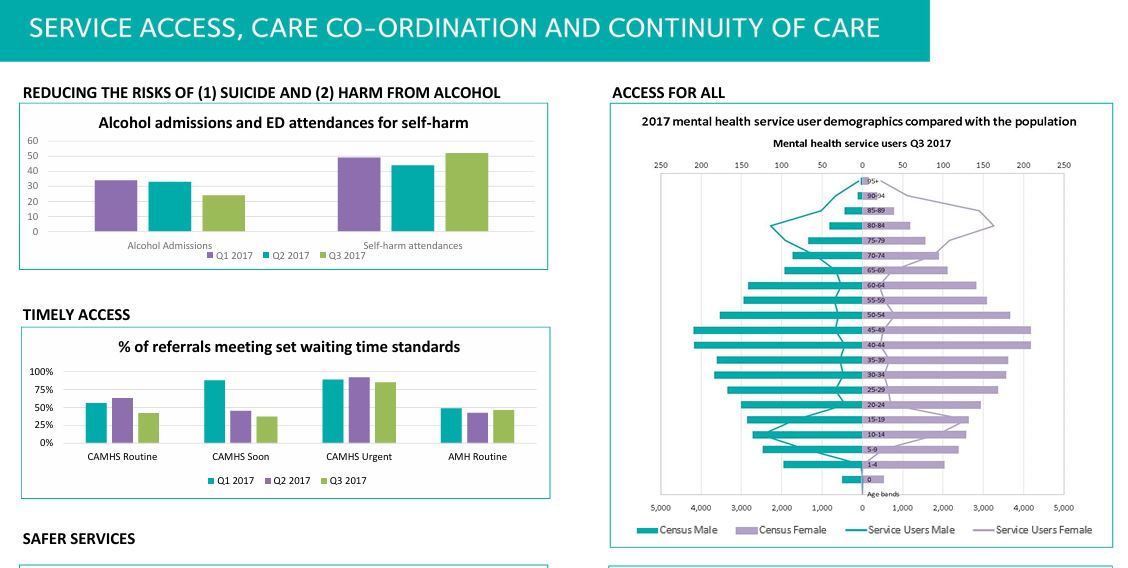
**4.11.3 Psychological Health and Safety Dashboard (New Zealand Resource)**

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 organisations in recognising data that is relevant to them and to visualise 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 optimised 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 realising 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 updated and continues to be (annually or biannually), which could cause a delay in identifying the emerging mental health issues or their 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 Customised 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 beliefs 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 organisational level (Dewa & Hoch, 2015).

Filter and analyse 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 organisational 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 organisations 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 employees’ 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 Organisational Context and Systems**: Organisational 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 organisation 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, organisations sometimes lack the in-house capability to design, update and interpret any complex mental health indices (Pearson, 2024).

**4.15 Examples of Methods Useful in Creating Dashboards**

This section describes certain methods useful in creating an effective dashboard. To create a comprehensive dashboard structure that would help to monitor the mental health of employees and contribute to organisational decision-making, one can rely on a similar complex of data engineering and statistical modelling techniques and methods of machine learning (Raschka et al., 2022). On the data ingestion step, the information is worked out of surveys of employees, HC systems, wearables, and communication tools (Microsoft Graph API, Slack API), presenting up-to-date data concerning mood, absenteeism, engagement, and collaboration (De Choudhury et al., 2013; Sun & Medaglia, 2019).

The preprocessing part of data establishes the quality of data to be analysed, where methods like Z-score normalisation, time-windows, and aggregation and missing data imputation (involved to avoid missing data, for instance, k-NN or MICE) are used (Raschka et al., 2022). BERT and VADER represent Natural Language Processing (NLP) models that can be used to analyse qualitative comments to acquire the sentiment and feelings trends among employees through surveys and digital messages (Hutto & Gilbert, 2014; Devlin et al., 2019). To extract themes in free-text responses, the topic modelling techniques such as the Latent Dirichlet Allocation (LDA) and BERTopic are typically employed (Blei et al., 2003).

Machine learning models are used to predict burnout, turnover, and the risk of mental health at the analytical level, including logistic regressions, random forests, and gradient boosting (XGBoost) (Chen & Guestrin, 2016). In case of unsupervised learning, such as K-means or DBSCAN, well-being patterns of employees may be split into distinct groups in order to facilitate interventions (Zahra & Asghar, 2023). Also, there are anomaly detection algorithms where the behavioural data deviations are detected by means of such algorithms, known as Isolation forest and One-Class SVM, which give early warning notifications (Agyemang, 2024).

To visualise data, the dashboard platform, such as Power BI, Tableau, or Dash, allows interacting with mental health metrics, including the engagement scores, workload stress levels, and absenteeism patterns, in real-time. The platform is mostly equipped with alert seeds about dynamic thresholds and visual features, including heat diagrams or line graphs (Sun & Jung, 2024; Dilla et al., 2010). There is the multi-criteria decision analysis (MCDA) and rule-based systems to guide the actions of the HR, and also the linear programming models can be put into place so as to optimise the use of mental health resources as an objective of decision-making (Pardede, 2019).

More importantly, methods that enable privacy should be included in the dashboard. These are differential privacy, k-anonymity and data masking to mask the identity of the employees without reducing aggregate inferences (Dwork, 2006). FP is still under development, and in extreme cases, federated learning can be used to allow modelling without the centralisation of sensitive information (Yang et al., 2019).

**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 Summary**

This review provides a valuable and time-relevant way of using data analytics to achieve employee mental health monitoring and optimisation. The framework combines multi-source data (surveys, communication tools, and wearable devices) to furnish real-time dashboards with visualisation of important well-being aspects. The paper highlights the importance of having machine learning techniques such as clustering, anomaly detection, and topic modelling for interpreting actionable knowledge out of both structured and unstructured data.

The review further describes how decision-support systems, like multi-criteria decision analysis (MCDA) and optimisation models, can be put into effect to inform HR interventions and resource distribution. The framework provides a scalable framework to organisations that want to establish data-oriented cultures that put a weight on mental health and strategic choices, achieved through the integration of technical rigours and real-world practicality. The project is within the emerging sphere of digital well-being and fits the international tendency in workforce management to be proactive and evidence-based.

**5.3 Key Recommendations**

For an efficient Mental Health Index Dashboard to be constructed that enables effective organisational decision-making and improves the health state of the employees, we need to conceptualise 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 prioritised. 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, anonymised, stored and used in the proper way, and organisations 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 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.

**5.4 Future Work**

Future works can focus on the following:

**Building of Integrative Frameworks**

There is an urgent need to have elaborate frameworks which encompass user-centred design and principles, coupled with best practices and practical guidelines on how to create a dashboard. Subsequent research should focus on producing in-depth work, which describes the step-by-step dashboard design process, starting with the deepest knowledge of requirements, down to the implementation and continual reviews. Such frameworks need to be moulded to fit several organisational situations, with consideration being given to industry-specific needs and challenges.

**Advanced Integration Analytics**

Since many organisations are finding ways to gain more insights from their data, the future aspect in research is integrating advanced analytics capabilities into interactive dashboards. It may include researching the application of machine learning algorithms, predictive analytics, and data mining methods.

**User Behaviour and Engagement Exploration**

The knowledge base on the user behaviour relevant to interactive dashboards is significant in enhancing their design as well as functionality. Researchers should focus future research on exploring the influence of varied user demographics, along with roles, on engagement levels and preference toward features of dashboards. Using the interaction pattern with the dashboards, researchers are able to come up with the best practices on how to customise dashboards with regard to the different needs of the stakeholders in an organisation.

**Longitudinal Impact Studies**

Although this study has given an insight regarding the immediate benefits of the introduction of interactive dashboards, future work ought to be done on longitudinal studies, which would enable assessing the effectiveness of the tool on organisational performance over the long term. Assessing the impact of dashboards on decision-making in the long run, scientists may detect patterns, quantify the levels of consistent engagement, and even trace the changes in user behaviour. This would assist the organisations in getting a good idea of what their dashboard investments are worth and how they could improve in future.

**Cross-industry Comparisons**

Comparisons with dashboard implementation across industries would also be a good idea to conduct in the future. Interactive dashboards offer numerous opportunities for researchers can identify challenges, opportunities, and success factors in various industries.

***Ethical Standards***

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

***Disclaimer (Artificial intelligence)***

Authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT) and text-to-image generators have been used during the writing or editing of this manuscript. However, the Grammarly application was used for correcting some grammatical errors.

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