Mental well-being through HR analytics: investigating an employee supportive framework

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Abstract

Purpose – Organisations are increasingly adopting and adapting to technological advancements to stay relevant in the era of intense competition. Simultaneously, employee mental well-being has become a prominent global concern affecting people across various demographics. With this in mind, the present study explores the influence of human resource (HR) analytics, mental health organisational evidence-based management (OEBM) and organisational mental health support on the mental well-being of employees. Additionally, the study examines the moderating effects of manager and peer support on the association between organisational mental health support and the mental well-being of employees.

Design/methodology/approach – Data were collected from 418 employees in India and structural equation modelling was performed to analyse the data.

Findings – The study found significant positive associations between HR analytics with mental health OEBM, organisational mental health support and mental well-being. Mental health OEBM was also found to be positively related to organisational mental health support and mental well-being. The moderating roles of manager and team support were also found to be significant in the associations between organisational mental health support and well-being.

Originality/value – The study showed that HR analytics is a valuable source of mental health data. This data can facilitate the development of evidence-based management (EBM) strategies to promote the mental well-being of employees.

Keywords HR analytics, Mental health, Mental health OEBM, Mental well-being

Paper type Research paper

Introduction

Researchers and practitioners are increasingly interested in studying and utilising data, technology and advanced analytical tools to support various organisational activities (Ferraris et al., 2019; Edwin Cheng et al., 2022). This is driven by the perception that technology and emerging analytical domains like HR analytics (Xu et al., 2016; Cao et al., 2019) and supply chain analytics (Dubey et al., 2021; Agrawal et al., 2022) can empower organisations to make decisions more rapidly and with greater precision (Marler and Boudreau, 2017; Chalutz Ben-Gal, 2019). These analytics-driven decision-making approaches predominantly focus on organisational outcomes, such as performance (Mikalef et al., 2019; Rialti et al., 2019; Mikalef et al., 2020), business value (Grover et al., 2018; Mikalef et al., 2020) and innovation (Duan et al., 2020; Akter et al., 2022).

In the current uncertain business environment fraught with stiff competition and rapid employee turnover, organisations heavily rely on employee data and human resource (HR) analytics to predict organisational outcomes (Tursunbayeva et al., 2018). Thus, organisations have been actively adopting and adapting to technological advancements and analytical tools to enhance performance (Sivathanu and Pillai, 2018; Claus, 2019).

Among the numerous tools available today, HR analytics has garnered significant interest as a powerful means of predicting organisational outcomes and facilitating efficient decision-making (Belizón and Kieran, 2022). While recent research in HR analytics has predominantly focused on organisational success and job-related outcomes like job performance...
few studies have explored its potential contributions to employee mental well-being. Given the rising concerns regarding mental health among employees, ranging from psychological distress to suicidal ideation (Lathabhavan et al., 2021; Hastuti and Timming, 2023), the present study investigates the possible ways in which HR analytics can be used to enhance the mental health of employees.

Although studies in evidence-based management (EBM) are common in health care services, they have been less frequently used in organisational settings (Martelli and Hayirli, 2018; Nicola et al., 2020). EBM involves making organisational decisions based on the best available scientific evidence and social science research (Hulpke and Frommueller, 2022). Recently, there has been a growing interest in exploring EBM from an organisational perspective, with a focus on organisational evidence-based management (OEBM) supported by HR analytics resources (Nicola et al., 2020; Mccartney and Fu, 2022).

Despite discussions on EBM in the context of mental health, there have been limited studies addressing the mental health aspects of employees within this framework. Addressing this research gap, the present study introduces the concept of mental health OEBM. This approach involves making decisions and categorisations related to mental health based on available evidence from data, incorporating findings from mental health research and HR analytics data within organisations to derive results.

Organisational support and facilities are important factors that affect employees’ mental well-being in an organisation (Aldamman et al., 2019). Mental health stigma persists in many countries, impacting the way people perceive and discuss mental health-related issues (Lathabhavan and Vispute, 2022). Introducing mental health assistance facilities within organisations can effectively eliminate this stigma and encourage employees to seek help when needed. Support from colleagues and leaders within the immediate circle also plays a significant role in understanding mental health (Cheng et al., 2020).

While studies have individually explored concepts like organisational support, leader support and peer support to predict mental well-being in various contexts (Payne et al., 2018; Farahnak et al., 2020; Ibrahim et al., 2020), there have been fewer studies that have examined the combined effects of these variables in the organisational setting for predicting mental well-being. As situational factors also play a vital role in predicting individual well-being, considering these factors together can provide a more comprehensive understanding of welfare (Yue et al., 2022). Considering this, the present study investigates the moderating effects of peer support and leader support in the association between organisational support and mental well-being.

In effect, this study aims to fill the research gap by examining the following associations: (1) the HR analytics and mental health OEBM, (2) mental health OEBM and organisational mental health support, (3) Organisational mental health support and mental well-being and (4) the moderating roles of leader support and peer support.

This research makes significant contributions to the fields of HRM and mental health in several ways. First, it highlights the potential of HR analytics to serve as a valuable source of mental health data, which can be utilised to enhance the well-being of employees. Second, the research analyses the role of mental health EBM within organisations, demonstrating the capacity to predict the mental well-being of employees using inputs from HR analytics. Third, it sheds light on how mental health EBM can effectively forecast and customise organisational mental health support to better predict mental well-being. Finally, the research identifies the moderating associations of leader support and peer support in the connection between organisational mental health support and mental well-being, thereby providing a deeper understanding of how these factors influence each other.

These findings collectively present valuable insights for HRM practices and mental health interventions in organisational settings. Figure 1 depicts the proposed model of the study.
Theoretical background and hypothesis development

The present study presents a research model that takes into account technological advancements, particularly HR Analytics, as a supportive tool for employee mental health, drawing theoretical support of Resource Based View theory (Barney, 1991). According to this theory, organisations must develop strategies to focus on all resources to enhance competitive advantage (Verhoef et al., 2021). In today’s highly dynamic environment characterised by volatility, uncertainty, complexity and ambiguity (VUCA), both technology and human resources are viewed as valuable assets, crucial for gaining a competitive edge (Zhang-Zhang et al., 2022).

In such a context, organisations emphasise a knowledge-intensive environment and heavily rely on human resources to create value (Qaiyum and Wang, 2018). Particularly after the outbreak of the COVID-19 pandemic, there has been an increasing focus on people-centric approaches, with a special emphasis on the mental well-being of employees, which is seen as a potential source of competitive advantage (Zhang-Zhang et al., 2022). With this understanding, this study connects technology to positive mental health by linking HR analytics with employee mental well-being.

HR analytics and mental health organisational evidence-based management (OEBM)

Digital transformation has propelled organisations to adopt data-driven approaches in various HR activities, including recruitment and selection, performance appraisal, diversity management and workforce planning (Hamilton and Sodeman, 2020; Tursunbayeva et al., 2022). The practice of using workforce data for decision-making goes by different names, such as HR analytics, people analytics, talent analytics, workforce analytics and human capital analytics, among others (Mccartney and Fu, 2022).

HR analytics is an emerging area of research both among academicians and practitioners (Huselid, 2018). It involves the systematic identification and quantification of the people-related factors that impact business outcomes and enable organisations to make informed and improved decisions (van den Heuvel and Bondarouk, 2017). In the context of the resource-based view (RBV), HR analytics is recognised as a valuable resource that allows
organisations to make data-driven decisions to address challenging problems among employees, ultimately leading to a competitive advantage (Marler and Boudreau, 2017; Minbaeva, 2018).

OEBM is a dynamic process that involves gathering and interpreting evidence as the basis for managerial decision-making within the organisation (Martelli and Hayirli, 2018). HR analytics generates evidence and organisational data that can be strategically utilised to facilitate EBM (McCartney and Fu, 2022). While employee mental health has gained attention in recent years, particularly in fields like healthcare (Sasaki et al., 2020; Bufquin et al., 2021), few studies have explored the technological inputs for mental health evidence from an organisational perspective.

As HR analytics can positively impact the organisational EBM (McCartney and Fu, 2022), the present study extends it to a more specific area of mental health. Supported by the RBV, the study posits that inputs from HR analytics can serve as a valuable resource in obtaining better evidence regarding employee mental health and, consequently, enabling effective management. Building on this literature support, the first hypothesis of the study is formulated as follows:

\[ H1. \] HR analytics is positively associated with mental health OEBM.

**Mental health OEBM and mental health organisational support**

The workforce is the intellectual capital of any organisation. The health and well-being of its workforce, including positive mental health, are of paramount importance to the health of the organisation (Lathabhavan et al., 2021). Usually, decision-makers rely on subjective methods like “gut feeling” or past experiences to understand and address employee mental health and well-being issues (Martin et al., 2018). Although evidence-based practices are common in mental health care service (Kilbourne et al., 2018; Stuijfzand et al., 2020), an evidence-based approach to mental health data from an organisational perspective has not been extensively explored.

This study introduces the concept of Mental Health OEBM as a dynamic process that involves collecting and interpreting evidence from mental health data, serving as the foundation for decision-making. Drawing upon EBM theory, the research argues that evidence and organisational facts generated by HR analytics can be leveraged to facilitate EBM, particularly in the realm of mental health. Employing EBM for mental health can lead to effective mental health support, either by managing the issues proactively or identifying the need for timely intervention (Clark, 2018). As described by RBV, organisations face challenges in making critical decisions to improve organisational success, which makes it essential to prioritise the mental health of employees alongside other skill development initiatives (Bergh et al., 2019). Considering the literature support, the second hypothesis is framed as:

\[ H2. \] Mental health OEBM is positively associated with organisational mental health support.

**HR analytics and organisational mental health support**

In recent years, organisations are increasingly focusing on promoting positive mental health among employees (Aldamman et al., 2019). Recognising that employees are the intellectual resources of the organisation, maintaining their positive mental health is crucial for achieving the organisational goals (Johnson et al., 2020). Emphasising this aspect, technological advancements have begun contributing to the analysis and understanding of employee mental health, particularly in the wake of the COVID-19 pandemic (Vizheh et al., 2020). This has paved the way for the use of analytics in the realm of mental health (Chung et al., 2020).
The increasing accessibility of mental healthcare data underscores the importance of informed decision-making based on stronger evidence (Chung et al., 2020; Richards et al., 2022). The data must accurately depict the complexity of mental healthcare, including its intricate interplay with factors such as structure, processes and outcomes (O’Neill et al., 2019; Chung et al., 2020; Kaveladze et al., 2022).

HR analytics is a powerful tool to predict employee at in various stages of their careers (Khan and Tang, 2017). The pandemic period witnessed increasing support of HR analytics towards mental health support, as the pandemic raised issues related to employment uncertainty and negative thoughts (Hastuti and Timming, 2023; Cooke and Xu, 2023). Moreover, supportive technologies that do not elicit concerns related to identity threat and stigma associated with mental health concerns, also ensure a comfortable environment for the employees (Brouwers et al., 2020; Xing et al., 2021). As supported by RBV, HR analytics, considered a valuable resource, collaborates with another key resource, namely employees, to promote positive mental health and, in turn, attain a competitive advantage (Singh et al., 2022). Based on this literature support, the third hypothesis is framed as:

**H3.** HR Analytics is positively associated with organisational mental health support.

**Mental health OEBM and mental well-being**

EBM is widely used within the healthcare domain for various types of diagnosis and decision-making processes (Martelli and Hayirli, 2018). However, this approach remains less explored in the organisational context. Managers can utilise evidence from past data, especially in cases concerning mental health, to implement supportive measures based on previous scenarios (McCartney and Fu, 2022). By adopting this approach, organisations can proactively address the mental health concerns of employees, either by implementing appropriate remedies or foreseeing potential issues (Johnson et al., 2020). According to the RBV, the support of resources in collecting information from past cases and applying it to future scenarios enhances competitive advantage by maintaining positive welfare and reflecting it in their work and professional behaviour. This holistic approach recognises the significance of employee mental health and its influence on organisational outcomes and overall performance.

Based on this literature support, the fourth hypothesis is framed as:

**H4.** Mental health OEBM is positively associated with mental well-being.

**HR analytics and mental well-being**

The use of technological and analytical support for addressing mental health concerns gained significant acceptance during the pandemic (Figueroa and Aguilera, 2020). Organisations also started relying on analytics to predict and find solutions for mental health issues (Hastuti and Timming, 2023). Studies have shown that technology facilities in the mental health domain effectively support the mental well-being of users (Anttila et al., 2021; Grovè, 2021). Technology-based analytics is useful in that it can analyse and provide potential information about a larger number of employees than the human handling of such issues (Singh and El-Kassar, 2019). HR analytics has also been found to positively impact employee and organisational outcomes (Marler and Boudreau, 2017; Quddus Mohammed, 2019). In alignment with RBV, analytics or technology as a resource can facilitate individual employee outcomes, contributing to the organisation’s competitive advantage (Khanra et al., 2022). Based on this literature support, the fifth hypothesis formulated as:

**H5.** HR Analytics is positively associated with mental well-being.
Organisational mental health support and mental well-being

Recent studies have shown that organisational support positively influences employee performance (Martin et al., 2018; Aldamman et al., 2019). Given the significance of well-being in driving performance, organisations have begun to focus on employee health through various approaches (Haddon, 2018). Moreover, organisations have explored how welfare can act as a catalyst for both individual and organisational outcomes (Ruggeri et al., 2020; Alrawadieh et al., 2022). Sharing a positive experience or a current lived experience can also foster a more inclusive environment and improve welfare (King et al., 2023). Hence, the support provided by organisations indeed plays a crucial role in influencing the mental well-being of employees (Aldamman et al., 2019). However, while organisational support has been studied in a general or broader sense, its specific impact has often been overlooked (Aldamman et al., 2019).

The present study specifically considers the mental health support provided by organisations. It is undeniable that a supportive mental health facility can enhance the well-being of people (Lathabhavan and Sudevan, 2022). Yet, few studies have investigated the effects of organisational mental health support on the well-being of employees. Considering the literature support, the sixth hypothesis is proposed as:

\[ H6. \text{Organisational mental health support is positively associated with mental well-being.} \]

Moderating roles of manager support and team support

Manager support is indeed a vital factor in defining welfare (Salas-Vallina et al., 2021). Existing scholarly works have primarily investigated the manager’s role in welfare, either as an antecedent or a consequence of organisational outcomes (Hendriks et al., 2020; Haque, 2021). Studies focusing on mental health have also highlighted the importance of the manager’s role in promoting welfare (Petrie et al., 2018; Nielsen and Taris, 2019).

As presented by RBV, employees are the intellectual resources who collectively define the success or failure of organisations. Thus, each employee’s mental well-being is essential for the success of the organisation (Ipsen et al., 2020). A supportive manager can enhance the well-being of the employees, especially if the employees are going through tough times, along with proper mental health facilities (Nielsen and Taris, 2019). Likewise, support from colleagues is also a determinant of the mental health of employees (Gillard, 2019). Team members, through frequent communication and understanding, can better comprehend an employee’s mood patterns, job-related difficulties and other issues, thus enabling employees to manage matters more efficiently and regain mental well-being (Wolter et al., 2019; Hameed Shalaby and Agyapong, 2020).

The study aims to explore the rarely discussed moderating roles of both manager support and team support in the context of organisational mental health support in defining welfare. Based on this consideration, the following hypotheses were framed.

\[ H7. \text{Manager support moderates the association of the organisational mental health support and mental well-being, such that the relationship is stronger and positive when there is high level of manager support.} \]

\[ H8. \text{Team support moderates the association of the organisational mental health support and mental well-being, such that the relationship is stronger and positive when there is high level of team support.} \]

Method

The study used a cross-sectional design to investigate the hypothetical research model. Data were collected from 418 employees working in Indian organisations. Participation in the
survey was voluntary and electronic informed consent was received from each participant. The average age of the participants was 38.77 years (SD = 9.12). The sample comprised 223 men (53.35%) and 195 women (46.65%).

**Measures**
The survey instrument used in this study included seven measured constructs. All the measures were carefully selected and validated from prior previous studies to fulfil the objectives of the present study. All the items were measured on seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree").

**HR analytics** was assessed considering a 13-item scale (Mccartney and Fu, 2022). A sample item was “The employee data we have is collected on a regular basis”. The Cronbach’s alpha reported for this was 0.89.

**Mental health Organisational EBM** was assessed using a 6-items scale (Barends, 2015). A sample item was “We systematically search for and retrieve the best available evidence on mental health”. The Cronbach’s alpha reported for this was 0.86.

**Organisational Mental health support** was assessed using a 3-item scale on mental health perspective (Eisenberger et al., 1986). A sample item was “Mental health help is available from my organisation when I have a problem”. The Cronbach’s alpha for this was 0.88.

**Manager support** was assessed using a six-item scale (Vallières et al., 2018). A sample item was “My manager meets with me regularly to discuss problems and solutions”. The Cronbach’s alpha value was 0.91.

**Team support** was assessed using a seven-item scale (Rodwell et al., 1998). The sample item was “There is a lot of support and encouragement within my work group”. The Cronbach’s alpha value was 0.84.

**Mental well-being** was assessed using a 14-item scale (Tennant et al., 2007). A sample item was “I’ve been feeling good about myself”. The Cronbach’s alpha value was 0.88.

**Data analysis.** The study used Structural Equation Modelling (SEM) methods to test the research model, which was implemented in AMOS 24.0 (Arbuckle, 2016). SEM is best suited for evaluating multiple interrelated dependent relationships in the research model (Hair et al., 2009). Confirmatory factor analysis was performed with maximum likelihood estimation, to examine the accuracy of the proposed model. The goodness of fit of the model was evaluated using $\chi^2$ test static, the relative chi-square ($\chi^2$/df), the Root-Mean-Square Error of Approximation (RMSEA), Standardised Root Mean square Residual (SRMR), the Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI). Values larger than 0.90 for CFI and TLI, lower than 3 for $\chi^2$/df and 0.08 or lower for RMSEA indicated acceptable fit (Hu and Bentler, 1998; Byrne, 2013). RMSEA values of 0.05 or less indicated the close fit of the model (Browne and Cudeck, 1992).

**Results**

**Reliability and validity analysis**
The initial assessment involved analysing the internal consistency, convergent validity and discriminant validity of all variables to evaluate the measurement properties of the constructs. Table 1 presents the psychometric properties of all constructs considered in the study. The item loadings were above 0.60, and the Average Variance Extracted (AVE) values were above 0.50, indicating excellent content validity and convergent validity, respectively, for all measures. Moreover, the AVE values were found to be higher than the Maximum Shared Variance (MSV), signifying the strength of AVE and confirming the threshold for discriminant validity (Hew and Syed Abdul Kadir, 2016). The composite reliability values of all latent variables were above 0.75 and deemed adequate. The values of Cronbach’s alpha ranged above the critical level of 0.70 (Nunnally, 1994).
Discriminant validity was assessed using Table 2, which presents the correlation matrix for all constructs. The diagonals show the square root of AVEs. The square roots of all AVE scores were greater than their corresponding inter-correlations, indicating the presence of

<table>
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<th>Construct</th>
<th>Items</th>
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<th>Loadings</th>
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<th>AVE</th>
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<td>1.12</td>
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<td></td>
<td>MW3</td>
<td>4.22</td>
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<tr>
<td></td>
<td>MW9</td>
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<td>MW12</td>
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Table 1. Measurement model results

Source(s): Authors own creation
discriminant validity. Based on the above values, it can be inferred that the measurement model exhibited an adequate level of reliability and validity.

**Measurement models**

To assess unidimensionality and minimise measuring bias, goodness-of-fit indices such as $\chi^2/df$, Goodness-of-Fit Index (GFI), CFI and RMSEA were used. A full measurement model was tested using three pre-calculated variables (data quality, analytical capability and strategic ability to act) loaded on one general factor representing data analytics. The items of other constructs were loaded respectively to each construct. The six-factor model showed a good model fit with $\chi^2/df = 1.62$, $p < 0.001$; GFI = 0.95; CFI = 0.94; RMSEA = 0.04.

**Common method bias (CMB) analysis**

Harman’s single-factor test was conducted to check for Common Method Bias (CMB). Factor analysis using SPSS was performed, in which all the items were loaded with a threshold to attain one factor. The results showed that a single factor contributed to 24.13% of total variance extracted, which was well below 50%. This confirms that CMB was not a major concern for this study.

To further evaluate the CMB issue, the study employed the marker variable method. In this approach, “digital leadership” was selected as the marker variable, representing the leader’s ability to create a clear vision for the digitalisation process and execute strategies to achieve it. The marker variable was chosen as it is theoretically unrelated to the constructs in the research model.

A comparison analysis was conducted between the baseline model, which did not include the marker variable and the CBM test model with the marker variable (Malhotra et al., 2006). The results showed that there were no significant differences in terms of path coefficients and explained the variance between the original model without the marker and the test model with the marker variable. Furthermore, the marker variable had no significant influence on the endogenous variables. Based on the statistical analysis results, it can be concluded that CMB was not a serious problem in the study, and the marker variable method confirmed the absence of CMB.

**Structural models**

Table 3 presents the results of the hypotheses testing with direct associations in the model. The data were analysed using SEM to test the proposed hypotheses. As shown in the table, the association between HR analytics and Mental health OEBM was found to be positive and significant ($\beta = 0.26; p < 0.01$), thereby supporting H1. Similarly, the association between

<table>
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<th>3</th>
<th>4</th>
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<td>3. Orgl. Mental health support</td>
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<td></td>
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<td>4. Manager support</td>
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<td>6. Mental Wellbeing</td>
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<td>0.24</td>
<td>0.13</td>
<td>0.19</td>
<td>0.81</td>
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</table>

**Note(s):** The diagonals value represents $\sqrt{AVE}$

**Source(s):** Authors own creation

Table 2. Descriptive statistics of measures (N = 418)
Mental health OEBM and organisational mental health support was found to be positive and significant ($\beta = 0.27; p < 0.01$), supporting H2.

Furthermore, HR analytics showed a positive association with organisational mental health support ($\beta = 0.28; p < 0.01$), thus supporting H3. In line with hypothesis H4, the association between mental health OEBM and mental well-being was found to be positive and significant ($\beta = 0.22; p < 0.001$), and thus, the hypothesis was accepted. Similarly, HR analytics demonstrated a positive association with mental well-being ($\beta = 0.29; p < 0.01$), supporting H5. Additionally, the association between organisational mental health support and mental well-being was found to be positive and significant ($\beta = 0.24; p < 0.05$), supporting H6.

For the interaction effects, manager support was found to positively moderate the association between organisational mental health support and mental well-being ($\beta = 0.22; p < 0.01$). Hence, as seen in Figure 2, manager support augments the positive association between organisational mental health support and mental well-being. Likewise, team support was found to significantly moderate the association between organisational mental health support and mental well-being ($\beta = 0.17, p < 0.001$). The results suggest that team support enhances the effects of organisational mental health support on mental well-being. Refer Figure 3.

**Discussion**

**Theoretical implications**

The study contributes significantly to the existing literature and understanding in several ways. The first contribution of the study is that it validates the utility of HR analytics in gathering and processing the mental health data of employees in an organisation. This valuable information assists organisations in their efforts to enhance employee mental well-being and thereby organisational outcomes. Thus, it extends previous studies in the areas that analysed the use of HR analytics to predict suicidal ideation and behaviour (Hastuti and Timming, 2023; Wirges and Neyer, 2023). The novelty of this study is its employee-oriented approach to HR analytics, which aligns with the theoretical underpinning of RBV and the use...
of methodological support of serial mediation. As a result, this approach reinforces the importance of human resources as a competitive advantage for organisations.

The study’s second contribution is that it establishes the usefulness of HR analytics in the EBM of organisations. Although EBM exists in healthcare areas, EBM has hitherto not been explored to a great extent in the context of organisational operations (Mccartney and Fu, 2022). The study shows that HR analytics can be used for EBM, especially in the realm of mental health. By analysing the data, the study identifies evidence related to mental health concerns, symptoms and triggers, which can be used to design appropriate coping mechanisms (Arango et al., 2018). This extension of the EBM concept, commonly used in healthcare for evidence-based decision-making, is replicated in an organisational setting using employee data as the evidence (van Os et al., 2019; Mccartney and Fu, 2022).

The study’s third noteworthy contribution is its demonstration of how mental health EBM can accurately predict and tailor the mental health support facilities provided by organisations. This customisation leads to improved mental well-being among employees,
highlighting the significance of adopting evidence-based approaches in promoting mental health within the workplace.

The study’s extension of the EBM approach to determine mental health support and well-being is noteworthy. Additionally, the study uncovers the significance of not only organisational support but also the roles of managers and team support in predicting employees’ mental well-being. The novel contributions of the moderating roles of managers and team support offer valuable insights in the context of mental well-being research within organisations.

**Practical implications**
The present study has important implications for practitioners and organisations. By exploring the role of HR analytics as a valuable resource and tool to assess employees’ mental well-being, organisations equipped with advanced technological support can leverage data interpretations to gain insights into the mental health of their employees (Hastuti and Timming, 2023). Organisations can employ various tools or platforms, tailored to employees’ preferences and comfort, including options like chatbots (Abd-alrazaq et al., 2019), mental health apps (Alqahtani and Orji, 2020), websites and online mental health supports (Stawarz et al., 2019).

EBM help organisations understand various factors such as sleeping patterns and anxiety levels, which, in turn, can facilitate the implementation of effective mental health support activities (Johnson et al., 2020). Organisations must also prioritise data quality and the expert utilisation of data to investigate, analyse and address various issues (Pariona-Cabrera et al., 2022). Offering awareness sessions aimed at reducing the stigma surrounding mental health can encourage employees to share their concerns more openly, without hesitation (Clay et al., 2020). Innovative initiatives that encompasses peer support and organisational support can be promoted using technology, which could encouraging employees to disclose their mental health concerns without loss of privacy (Andalibi and Flood, 2021).

Organisations that foster a supportive system with dedicated mental health facilities and an inclusive culture, bolstered by both managerial and peer support, can greatly aid employees in coping with psychological distress. Moreover, policymakers and societies are encouraged to advocate for and promote mental well-being initiatives within organisations to support the overall mental health of employees. This study’s findings offer practical strategies to create a healthier and more supportive work environment that prioritises employee welfare.

**Limitations and future scope of the study**
The present study has a few limitations. First, the study’s cross-sectional design and reliance on self-reported data introduce the risk of CMB. Future research utilising longitudinal designs can mitigate this bias and provide more reliable and actionable findings over time. Secondly, the study focused on a specific cultural context, which may limit the generalisability of the results to other contexts. To enhance the model’s predictive capacity, future studies should incorporate additional relevant variables from diverse cultural settings. Lastly, the study examined a limited set of variables and only considered manager and team support as moderators. Exploring the distinct effects of technology and mental health aspects could provide further insights to further enrich the existing literature. Addressing these limitations can contribute to a more comprehensive understanding of the associations between HR analytics, mental health and organisational support.

**Conclusion**
The present study used RBV theory to examine the role of HR analytics in assessing and addressing the mental well-being issues of employees in an organisational setup and its usefulness in OEBM. The results revealed positive associations between HR analytics and
mental health OEBM, organisational mental health support and mental welfare. Additionally, the study found significant moderation effects of team and managerial support on the association between organisational mental health support and mental well-being. Beyond its theoretical contributions, the study explores the extensive potential of HR analytics in utilising technology to promote positive mental health and well-being among individuals. The study underscores the significance of prioritising employees’ mental well-being by combining technological advancements with human skills, which ultimately leads to successful organisations and happier societies.

References


About the author
Dr Remya Lathabhavan is an Assistant Professor of the Indian Institute of Management Bodh Gaya, India. Her research interests include glass ceiling, corporate social responsibility, human resource management, data analytics, artificial intelligence, career progression, mental health and psychology. She authored many articles and book chapters in peer-reviewed journals and books. Remya Lathabhavan can be contacted at: remya.l@iimbg.ac.in

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