



Application of Deep Learning Techniques for Detecting Digital Burnout among IT Professionals: A Systematic Review

Ashwini J. Shinde¹, Dr. Mrs. Yogita V. Bhapkar², Dr. Mrs. Swati Joshi³, Aarti A. Kulkarni⁴

¹Research Scholar Bharati Vidyapeeth (Deemed to be University) Yashwantrao Mohite College of Arts, Science & Commerce, Pune.
E-mail: ashwinitalekar171@gmail.com

²Bharati Vidyapeeth (Deemed to be University) Yashwantrao Mohite College of Arts, Science & Commerce, Pune.
E-mail: Yogita.bhapkar@bharativedyapeeth.edu

³PVG's College of Science and Commerce, Pune-09. E-mail: Swati.joshi@pvgcos.ac.in

⁴G.K. Raisoni College of Engineering and Management, Wagholi. E-mail: aartirakhi2006@gmail.com

Abstract:

Digital burnout is a Mental, Emotional and Physical stress caused by prolonged use of digital devices due to increasing work demands. Mostly, IT professionals face this vulnerability because they are totally dependent on the digital devices to complete their work. Digital burnout may lead to emotional exhaustion, reduced productivity, decreased job satisfaction, cognitive fatigue, and mental health concerns. To maintain a healthy environment in terms of well-being of employees and growth of organization, the early burnout detection becomes the necessity. The recent techniques like deep learning provide automatic analysis of complex data patterns from massive digital data. Deep learning models such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), can learn hidden patterns from app usage, screen activity, notification frequency, and behavioural logs without immense manual feature engineering. This systematic review mainly focuses on analysis of existing research on digital burnout detection, techno stress assessment, and behavioural analytics. To identify the findings, challenges, research gaps and future prospects to develop an intelligent burnout detection system, major databases were reviewed.

Keywords: Digital Burnout, Deep Learning, IT Professionals, Behavioural Analytics, Multimodal Learning, Burnout Detection.

Introduction

The nature of the work at work places is changing rapidly and it directly affects the performance of the employees. Mainly, the IT professionals spend long hours on digital devices like Computers, Mobile phones or Laptops. Although technology improves competence and optimization, excessive use of digital devices has created new health challenges. One of the most significant challenges is digital burnout. Digital burnout refers to physical, emotional, and mental exhaustion caused by prolonged exposure to digital environments. Employees often experience tiredness, stress and lack of motivation, reduced concentration, and decreasing work performance. Online or remote work models have increased digital dependency. Employees continuously remain connected through emails, messaging platforms, virtual meetings, and project management systems throughout the day. This continuous connectivity mainly affects employee's personal and professional life. Information overload and constant notifications can create cognitive stress. Digital burnout is the main concern in lives of both employees and organizations. Organizations may experience reduced productivity and increased employee churn. Traditional burnout assessment methods heavily depend on surveys and self-reported questionnaires. This assessment method is very useful but it is subjective and cannot provide continuous monitoring. Researchers are increasingly exploring data-driven methods for burnout detection. Behavioural data such as screen time, application usage, typing patterns, and communication activity provide valuable insights. Artificial Intelligence and machine learning techniques enable automatic analysis of such data. Deep learning has appeared as an optimistic approach because it can learn complex patterns from large datasets. Models such as CNN, LSTM, and Transformers have demonstrated strong performance in behavioural analysis. Deep learning techniques help to reduce the manual feature engineering and improve prediction competency. Researchers are also exploring multimodal frameworks that combine behavioural, psychological, and textual data. These approaches provide deep insights on employee well-being. Many studies use small datasets and lack real-world validation. Data gathering remains restricted due to privacy issues. Most existing systems operate offline rather than in real time. Personalized burnout detection remains underexplored. This review analyses the evolution of burnout detection techniques. It evaluates traditional, machine learning, deep learning, and multimodal approaches.

Background of the study:

As digitization increases, the problem of Digital burnout is also growing. Extensive research into Digital burnout has established a link between the condition and excessive use of technology, pressure associated with remote work, and information overload. The rapid evolution of AI, combined with the availability of behavioural data, is encouraging the development of automated digital burnout systems. Deep learning techniques are far more useful than currently available conventional approaches because they enable us to understand complex behavioural patterns in more efficient way.

Research Problem:

The rising prevalence of digital burnout is having negative consequences for IT professionals, impacting their productivity and mental health. Ultimately, this also affects the organization growth and performance. Existing approaches rely entirely on survey-based data, which does not support continuous monitoring. Therefore, there is a critical need to develop an intelligent, privacy preserving system capable of identifying digital burnout and associated risks by analysing behavioural and psychological indicators.

Objectives of the Study:

The primary objective in studying the existing literature is to conduct a detailed review of the research concerning digital burnout and stress detection among IT professionals. The main aim of my study is to analyse the use of machine learning techniques for predicting digital burnout including a comparative assessment of these methods and to evaluate their practical applicability. Moreover the focus is on analysing its practical applicability and potential utility in future research, with the aim of developing an accurate, real-time digital burnout detection system that also preserves privacy.

Significance of the Study:

This study will make a significant contribution to academic research by assisting in the identification of suitable databases and algorithms for evaluation. The findings will enable organizations to develop effective systems that support employee well-being and encourage the adoption of AI-based solutions capable of monitoring employee's mental health.

Literature Review:

The research papers published from 2019 to 2026 have been selected for the in depth analysis of the studies to conduct the systematic research review. Authentic and reliable research databases including IEEE Xplore, Scopus-indexed journals, PubMed, SpringerLink, Elsevier, ACM Digital Library, Nature, and Frontiers were utilized for this purpose. Based on an analysis of this research, a detailed review was carried out regarding the various technologies, datasets, machine learning and deep learning algorithms, and evaluation methods used to detect digital burnout, as well as their practical utility in the workplace. The literature review clearly shows that research has shifted from traditional survey-based methods of assessing digital burnout to modern techniques based on artificial intelligence. These modern methods attempt to identify digital burnout more accurately by combining different types of data, including behavioural data, psychological data, and other forms of multimodal data. This makes it easier and more effective to monitor employee's mental health continuously and implement necessary preventive measures. After reviewing the existing studies it indicates the extensive use of LSTM, CNN, Transformer, and Hybrid Deep Learning techniques. These techniques help to identify the digital device usage and user's behavioural aspects automatically, which are more accurate and reliable in prediction of Digital burnout.

Early research on burnout primarily based on statistical analysis and survey-based methods. The method developed by Maslach and Jackson to measure burnout is considered a significant milestone in the field. The Burnout Measurement Framework they created remains one of the most reliable and widely used tools for psychological assessment today. This same method is also extensively used to validate modern digital burnout detection. Tarafdar et al. [2] studied the concept of 'techno stress' and, using survey-based methods, elucidated the negative impact of technology on employee productivity. Similarly, Dragano and Lunau [3] conducted a comprehensive review of various studies on techno stress. Their research highlighted that techno stress is emerging as a significant and growing issue for employees in workplaces characterized by the increasing use of digital technology. Tams et al. [4] employed mixed research methods to study the positive and negative effects of technology usage on employees. This research contributed to a better understanding of the psychological aspects of digital burnout. However, these studies primarily relied on self-reported questionnaires; consequently, the findings are contingent upon individual's personal opinions and their accuracy may be affected to some extent by response bias.

In these methods, burnout is measured only at specific intervals. Consequently, it is not possible to continuously monitor changes in employee behaviour. Given the extensive use of technology by organizations in today's digital work culture, relying solely on these traditional methods is insufficient. This makes it increasingly difficult to identify digital burnout in a timely manner and implement the necessary preventive measures. Due to the rapid growth in behavioural data and computational intelligence, researchers have begun using machine learning techniques to identify digital burnout. Shatte et al. [7] reviewed various studies and highlighted the increasingly significant role of machine learning in predicting

mental health. Additionally, Kumar and Sharma [10] successfully employed the Support Vector Machine (SVM) algorithm to detect stress. Their study showed that SVM achieved more accurate classification compared to traditional statistical methods. Similarly, Singh and Varma [17] compared various machine learning algorithms and concluded that ensemble learning techniques enable more accurate prediction of burnout. Patel et al. [16] conducted a comprehensive review of various machine learning techniques used to detect stress. Additionally, Mehta et al. [22] attempted to predict digital burnout using behavioural analytics; for this purpose, they utilized behavioural features such as screen time, application usage frequency, and notification patterns. All this research indicates that, compared to traditional methods, machine learning algorithms offer more accurate predictions, scalability (the ability to handle large volumes of data), and automation. However, most machine learning models require feature engineering; this means that before training the model, researchers must manually select and construct key behavioural features associated with burnout. The performance of these models largely depends on the quality of the selected features. They often struggle to accurately capture complex nonlinear relationships and long-term temporal dependencies within behavioural data. Due to these limitations, researchers have focused on employing more advanced and effective deep learning techniques. Recent advancements in the field of deep learning have made the process of identifying digital burnout more effective. This technology enables the automatic learning of meaningful representations from raw behavioural data, thereby reducing the need for researchers to manually select or engineer individual features. Goodfellow et al. [1] established the theoretical foundation of Deep Learning. Their work paved the way for the effective application of Deep Learning techniques in various fields such as healthcare, behavioural analytics, and mental health. Chen et al. [18] demonstrated in their research that deep learning models are more effective and accurate than traditional machine learning methods for predicting mental health-related issues. Additionally, Wang et al. [24] and Iyer et al. [38] utilized Long Short-Term Memory (LSTM) networks to analyse behavioural time-series data. These models effectively identified temporal dependencies in individuals' digital device usage, enabling more accurate analysis and prediction of digital burnout. Kim et al. [19] utilized the Convolutional Neural Network (CNN) technique for emotion detection and achieved high prediction accuracy. Similarly, Nair et al. [39] proposed a CNN-LSTM hybrid architecture. In this model, spatial features (key characteristics of the data) are learned using the CNN, while temporal features (changes over time) are learned with the aid of the LSTM; this resulted in more accurate and reliable stress detection outcomes. Brown et al. [34] conducted a study on contextual emotion detection using Transformer-based models. Their research demonstrated that Transformer-based models exhibited superior performance in analysing textual behavioural data. All these studies indicate that, compared to traditional machine learning algorithms, deep learning models can identify important features in data (feature extraction) more effectively. These models demonstrate good performance on new data (generalization) and yield higher prediction accuracy. However, these models also have certain limitations. They require large amounts of labelled data, significant computational resources, and a long training period. Additionally, careful hyper parameter tuning is necessary to enhance the model's performance. Since most deep learning models operate as black boxes, it is difficult to clearly understand why a particular decision was made. This is considered a significant challenge, especially in the healthcare sector, where decision-making processes need to be transparent and easy to understand. Recent research increasingly emphasizes a multimodal approach to overcome the limitations of methods based on single-source data. This approach attempts to detect digital burnout more accurately by integrating behavioural, psychological, textual, and physiological data. Zhou et al. [26] developed a multimodal deep learning framework that integrates behavioural and textual information. Their research demonstrated that this integrated approach significantly improved the prediction accuracy for digital burnout. Similarly, Singh et al. [27] developed a hybrid burnout detection model that integrates behavioural data and psychological survey responses. Their research demonstrated that this model exhibited superior performance and accuracy compared to models based on only a single type of data. Park et al. [40] and Das et al. [46] emphasized the effectiveness of multimodal artificial intelligence techniques. According to their studies, integrating diverse types of information enables a better understanding of the complex aspects of human behaviour and allows for more accurate prediction of mental health-related issues. A study of available literature consistently indicates that the integrated use of multiple data sources leads to a deeper and more comprehensive understanding of digital burnout. The primary reason for this is that changes in an individual's behaviour do not stem from a single factor; rather, they are driven by a combination of psychological and contextual factors. However, there are also certain practical challenges associated with the use of multimodal systems. Key challenges include the simultaneous and proper integration of diverse types of information (data synchronization), handling incomplete information (missing values), increased computational complexity, high implementation costs, and privacy concerns arising from the collection of sensitive personal information. Due to these reasons, the large-scale use of such systems in real organizational environments remains limited at present. A review of the selected literature clearly indicates that methods for identifying digital burnout have witnessed significant advancements, ranging from traditional psychological assessments to advanced deep learning and multimodal techniques. Traditional methods enable a validated psychological assessment of burnout. Subsequently, machine learning techniques enhanced the predictive capability regarding burnout. Further advancements through deep learning models made automatic feature learning possible, thereby

significantly improving the accuracy of burnout detection and overall performance. Since multimodal methods utilize various types of information in combination, digital burnout can be predicted more accurately. Consequently, these methods are currently considered one of the most promising and rapidly evolving research directions in this field. However, a review of the literature reveals certain significant research limitations. These include the lack of real-time monitoring, a scarcity of systems customized to individual needs (limited personalization), insufficient longitudinal analysis, the need for privacy-preserving AI frameworks, the absence of explainable deep learning models, and a lack of validation based on data obtained from actual workplaces. To address these challenges, there is a need to develop digital burnout detection systems in the future that are more effective, reliable, and easily deployable within actual organizations. These findings clearly indicate the need to develop Deep Learning-based systems to identify digital burnout among IT professionals—systems that are intelligent, personalized, explainable in their decision-making processes, and privacy-aware. Such systems would enable more accurate, reliable, and timely diagnosis of digital burnout.

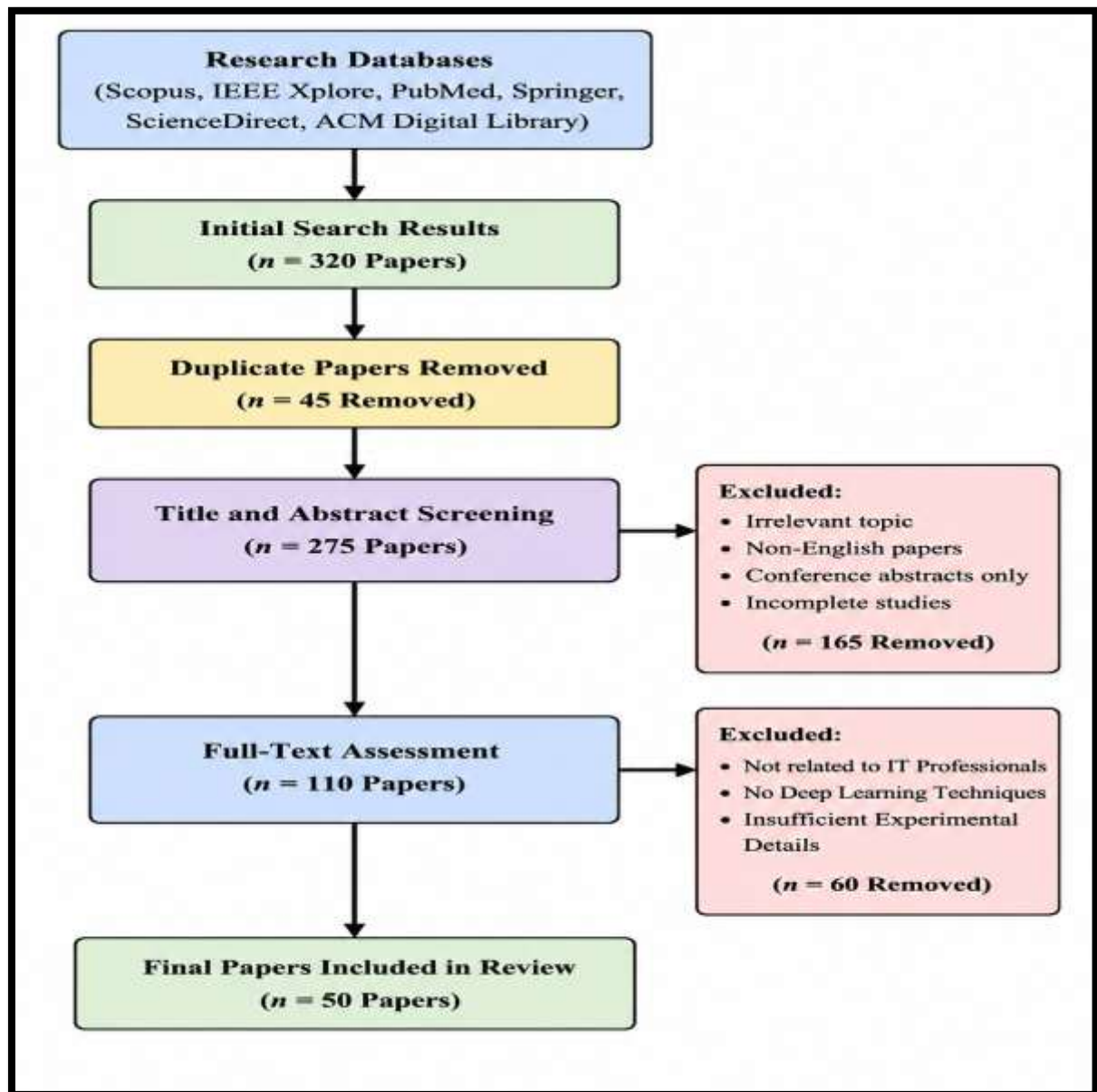


Fig 1. Criteria used for Systematic Review

Comparative Analysis and Critical Evaluation:

A review of the evolution of methods for identifying digital burnout reveals a shift from the traditional survey-based approaches used initially to advanced techniques based on Artificial Intelligence. Each method possesses its own distinct characteristics and limitations; consequently, the significance of each method varies depending on the research objective, available data, and practical application requirements. Traditional methods primarily utilize survey-based data. In this approach, individuals complete standardized questionnaires to assess levels of stress, fatigue, and burnout. These methods are easy to use, yield easily interpretable results, and are backed by reliable psychological assessment tools such as the Maslach Burnout Inventory (MBI). However, since these methods rely entirely on self-reported responses,

they tend to be somewhat subjective. Furthermore, they do not allow for the continuous monitoring of an individual's behaviour or the real-time diagnosis of digital burnout. Consequently, their utility is somewhat limited in modern, dynamic, and technology-driven workplace environments. To overcome these limitations, machine learning-based methods were adopted. These methods utilize structured data such as screen time, application usage, and information obtained from surveys. Machine learning algorithms such as Support Vector Machine (SVM), Random Forest, and Decision Tree provide more accurate predictions than traditional statistical methods. Furthermore, they possess the capability to analyse large datasets quickly and effectively. However, these methods require manual feature engineering. This means that before training the model, researchers must themselves determine which features are important and extract that information. Consequently, the ability of these models to automatically learn and understand complex behavioural patterns is limited. For this reason, recent research places greater emphasis on deep learning-based methods. These models can effectively analyse complex, time-varying behavioural data. Consequently, it becomes possible to predict digital burnout with greater accuracy and reliability. Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and hybrid deep learning models automatically learn essential features from raw data, eliminating the need for separate manual feature engineering. Consequently, these models more effectively identify temporal behavioural patterns associated with digital burnout and provide more accurate predictions compared to traditional methods. However, these models also have certain limitations. They require large amounts of labelled data, substantial computational resources, and extended training periods. Consequently, the computational cost associated with these models is relatively high, making their implementation somewhat challenging in resource-constrained environments. The most advanced approach is the multimodal-based system. These methods enable a more comprehensive assessment of digital burnout by integrating behavioural data, responses from psychological surveys, textual data, and sometimes physiological signals. By integrating various types of information, these methods provide a deeper and more comprehensive understanding of an individual's mental state. Consequently, compared to all other currently available methods, these systems are capable of making more accurate predictions. However, developing and practically implementing multimodal systems is relatively more complex. Key challenges facing these systems include the proper integration of data from diverse sources (data synchronization), increased computational complexity, and the protection of an individual's sensitive personal information (privacy protection). Overall, this comparative study indicates that traditional methods remain useful for psychological assessment. However, Machine Learning and Deep Learning techniques have made the process of detecting digital burnout more automated and accurate. Among these, systems based on Multimodal Deep Learning are emerging as the most promising direction for future research. Nevertheless, to effectively utilize these systems on a large scale, it is essential to find effective solutions to challenges such as privacy protection, scalability, and real time implementation.

Strengths:

A key advantage of deep learning techniques is their ability to automatically identify essential features. While researchers must manually select features in traditional machine learning methods, deep learning models autonomously learn relevant and significant patterns from raw behavioural data. Consequently, human intervention is reduced, and burnout can be predicted with greater accuracy. The Long Short-Term Memory (LSTM) deep learning model is considered particularly useful for identifying digital burnout. This is because LSTM can effectively learn long-term dependencies within sequential data. Consequently, it enables accurate analysis of daily screen time, application usage, notification frequency, and other time-series behavioural data. Recent research indicates that multimodal systems predict digital burnout more accurately by integrating various types of information. These methods incorporate behavioural logs, psychological survey responses, textual data, and physiological signals. Analysing all this information collectively enables a deeper and more comprehensive understanding of an individual's mental state. Consequently, it becomes possible to diagnose digital burnout more reliably and accurately compared to single-modal methods. Artificial Intelligence (AI)-based monitoring systems can identify early signs of burnout in a timely manner by continuously analysing user behaviour. This enables the implementation of necessary preventive measures before the issue becomes critical. Such systems allow organizations to more effectively safeguard employee mental health, reduce absenteeism, and help boost overall workplace productivity.

Limitations:

Despite all these advantages, certain significant limitations are observed in the available literature. Many studies have utilized small or limited datasets, making it difficult to effectively implement the developed models across large and diverse populations. Even if such models achieve high accuracy during the experimental phase, there is no guarantee that they will maintain the same level of performance in real-world application. Another significant limitation is the lack of real-time implementation. Most currently available digital burnout detection systems have been evaluated based on offline datasets or retrospective analysis. Consequently, their utility remains limited when it comes to continuously monitoring employee behaviour in the actual workplace to detect burnout in a timely manner and implement immediate interventions. A review of the literature has also highlighted significant issues regarding privacy and ethics. Systems used to detect digital burnout often require an individual's sensitive information. This includes

data on application usage, communication patterns, and mental health indicators. Consequently, the secure collection and appropriate use of such data, along with the protection of privacy, constitute a crucial requirement for future research. Secure data collection, anonymization of personal information, obtaining user consent, and adherence to ethical guidelines remain significant challenges in this field today. Many currently available models exhibit limitations regarding personalization, the ability to adapt to individual needs. Most systems employ a uniform model for all users; however, every individual differs in terms of work habits, digital usage patterns, stress tolerance, and lifestyle. Therefore, it is essential to develop personalized prediction models that take into account the unique characteristics of each individual. Such systems would enable more accurate prediction of burnout and allow for the provision of appropriate, user-specific recommendations. Another significant challenge is the limited validation of these models in real workplace environments. Many of the currently proposed systems have been tested only under controlled experimental conditions or using simulated datasets. Due to the constant changes within IT organizations, such as shifting workloads, evolving work cultures, changing schedules, and fluctuating employee behaviour, there has been relatively limited research and testing conducted under this model. Therefore, there is an urgent need to rigorously validate these models in real world workplace settings. A comparative study revealed that deep learning multimodal methods demonstrate significant progress in the detection of Digital burnout. However, there is still a significant need for improvement in areas such as real time monitoring, personalization, privacy preservation, and validation. If an effective solution is developed to address these challenges, it is possible to create a digital detection system for IT professionals that is highly reliable, accurate, and practical for real world use.

Research Gap:

A review of the available literature clearly indicates a significant shift in the methods used to identify digital burnout, moving from traditional questionnaire-based assessments to modern techniques such as Artificial Intelligence-driven behavioural analytics. However, several critical challenges persist regarding currently available systems, including scalability, interpretability (the ability to explain decision-making processes), and practical deployment in actual workplace settings. A detailed review of the literature reveals significant research gaps in digital burnout detection systems. These gaps limit the efficiency and practical utility of currently available systems. Many studies have independently analysed behavioural data such as screen time, application usage, and notification frequency. Some studies have assessed burnout using psychological surveys based on self-reports. However, the number of studies that utilize a combination of both types of data is relatively small. For instance, Mehta et al. [22] studied burnout using behavioural data, whereas Tarafdar et al. [2] and Tams et al. [4] assessed techno stress and burnout primarily through survey based methods. In contrast, Singh et al. [27] demonstrated that combining behavioural data with information from psychological surveys enables more accurate prediction of burnout. Consequently, there is a clear need for further research into multimodal integration, the combining of various types of data. Although numerous models based on machine learning and deep learning have been developed, most of them have been evaluated using offline datasets. Research by Kumar and Sharma [10], Chen et al. [18], Wang et al. [24], and Nair et al. [39] has primarily focused on model development and performance within controlled experimental environments. However, research into systems that detect burnout in real-time through continuous monitoring of actual user behaviour remains limited. Therefore, there is a need to develop intelligent systems capable of identifying burnout symptoms and facilitating timely intervention before the condition becomes severe. Another significant gap identified in the literature is the lack of personalized models—those tailored to individual needs. Most models developed in studies such as those by Patel et al. [16], Chen et al. [18], and Wang et al. [24] apply uniform criteria to all users. However, individuals differ in their digital usage habits, work methods, stress response capabilities, and lifestyles. Therefore, it is essential to develop personalized burnout prediction models that take into account the specific characteristics of each individual. Such models will enhance prediction accuracy and enable the provision of personalized guidance (user-specific recommendations) to each user. Existing literature places relatively less emphasis on longitudinal behavioural analysis. Mehta et al. [22], Wang et al. [24], and Iyer et al. [38] have analysed data collected over short periods. Consequently, information regarding changes in digital burnout and its progression over weeks or months remains limited. Long-term analysis can provide greater insight into the early stages of burnout, potentially enabling more effective early diagnosis.

Issues regarding privacy and ethics are also significant topics of research in this field. Zhou et al. [26], Park et al. [40], and Das et al. [46] have demonstrated that analysing various types of data in combination yields more accurate results. However, there has been limited discussion regarding privacy-preserving AI, secure data management, anonymization techniques, and ethical deployment. Since digital burnout detection systems utilize an individual's sensitive behavioural and psychological data, further research on this subject is essential. Finally, although the problem of digital burnout is prevalent, particularly in the IT industry, there is a relatively limited number of studies focusing specifically on IT professionals within existing research. Studies by Shatte et al. [7], Chen et al. [18], and Patel et al. [16] have utilized general datasets to predict mental stress and mental health outcomes; however, research based exclusively on data collected from IT sector employees remains limited. There is a need to develop a deep learning-based system specifically for IT professionals, taking into account factors such as work-related stress, constant

digital usage, long working hours, and professional pressure. Overall, the literature review clearly indicates a need to develop Deep Learning-based systems for identifying digital burnout among IT professionals systems that are intelligent, multimodal, personalized, privacy-aware, and capable of real-time operation. Such systems would enable more accurate, reliable, and timely diagnosis of digital burnout, as well as facilitate its effective application in actual workplace settings.

Proposed Framework:

The primary objective of the proposed framework is to develop an intelligent and efficient Deep Learning-based system to accurately identify digital burnout among IT professionals. This framework comprises five key layers. Working in coordination, these layers collect, process, and analyse data related to user behaviour and present the results to accurately predict digital burnout. The first level of this framework is the Data Collection Layer. The primary function of this layer is to gather necessary information from multiple sources. It automatically collects behavioural data—such as the user's daily screen time, application usage patterns, notification frequency, device usage duration, and application switching behaviour. Additionally, psychological data is collected through standardized questionnaires such as the Maslach Burnout Inventory (MBI) to more accurately assess the user's mental state. Integrating both behavioural and psychological data enables a deeper and more comprehensive analysis of digital burnout. The second level is the Data Pre-processing Layer. At this stage, the collected data undergoes necessary pre-processing before the model is trained. This process involves removing incomplete or inconsistent information (data cleaning), normalization to bring all data into a uniform range, appropriately handling missing values, and selecting or creating key behavioural features associated with digital burnout (feature extraction). Proper pre-processing improves data quality and enhances both model performance and prediction accuracy. The third level is the Deep Learning Layer, which is the core component of this entire framework. A hybrid deep learning model incorporating Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) has been proposed for this layer. The LSTM model effectively learns long-term dependencies and behavioural changes within sequential data. On the other hand, the CNN model automatically identifies important features from the collected behavioural data. Integrating these two models enables effective analysis of both temporal changes and complex data features; consequently, predictions regarding digital burnout are expected to be more accurate. The fourth level is the Burnout Prediction Layer. At this level, a trained deep learning model analyses the user's behavioural and psychological data to determine their risk of burnout. The system classifies users into various categories such as Low, Moderate, High, or Severe Burnout Risk. This classification enables both organizations and the individuals concerned to identify early signs of burnout in time and implement necessary preventive measures (timely interventions) at the right moment. The final stage is the Visualization Layer. At this stage, the effects of digital burnout are presented to the user in an easy-to-understand format via an interactive dashboard. This dashboard displays the Burnout Score, behavioural trends, and risk levels, along with personalized alerts for the user, presented through graphs and other graphical formats. This enables employees, managers, and healthcare professionals to easily grasp essential information. Furthermore, it facilitates the continuous monitoring of employees' mental health and makes timely decision-making easier.

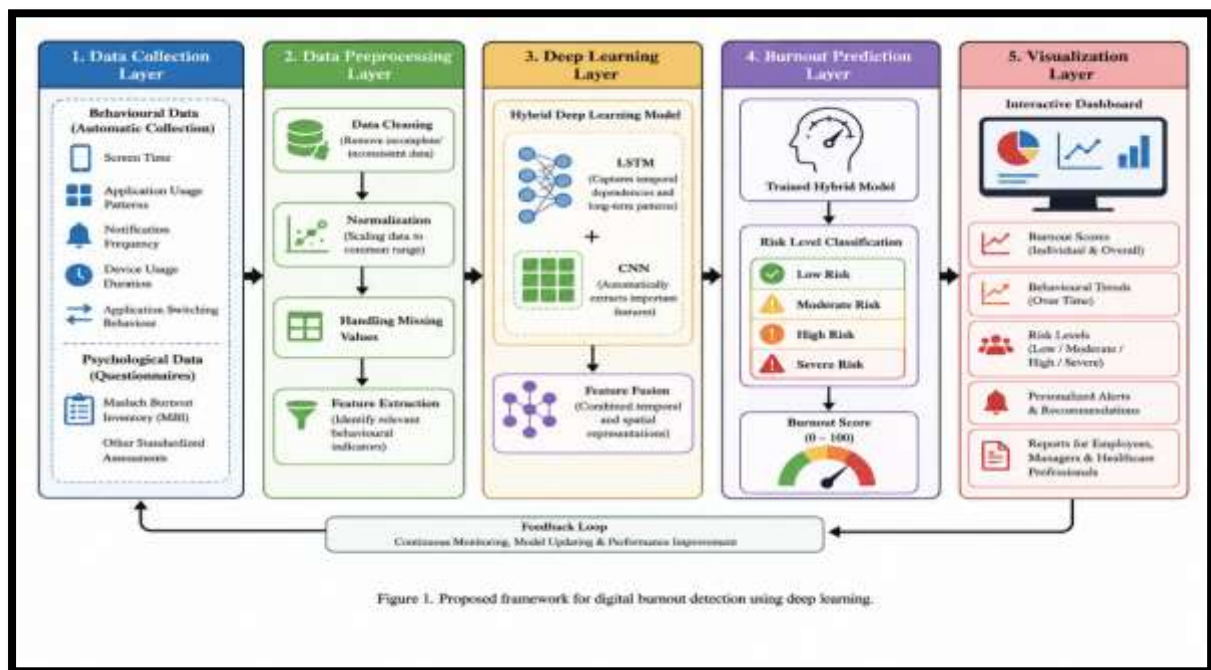


Figure 1. Proposed framework for digital burnout detection using deep learning.

Fig 2. Work Flow Flowchart

Methodology

This research adopts the Systematic Literature Review (SLR) methodology. The objective of this method is to conduct an in-depth and systematic study of existing research regarding the detection of digital burnout through the use of Artificial Intelligence, Machine Learning, and Deep Learning techniques. A defined and scientific approach was employed throughout the process for the search, selection, analysis, and comparison of relevant research. First, research articles were collected from Scopus, IEEE Xplore, PubMed, SpringerLink, ScienceDirect, ACM Digital Library, Nature, Frontiers, and other peer-reviewed research journals. This review includes only high-quality research articles published between 2019 and 2026 that are directly related to the topics of digital burnout, techno stress, stress prediction, behavioural analytics, machine learning, and deep learning. Conversely, duplicate articles, articles in languages other than English, editorials, and articles not directly related to the research topic were excluded based on predetermined inclusion and exclusion criteria. The selected research articles were then systematically studied and classified based on various criteria. These criteria included the type of dataset used (Behavioural, Psychological, Physiological, Textual, or Multimodal), the algorithms employed, the evaluation metrics used to measure performance, and the key research outcomes of each study. Various machine learning and deep learning techniques were employed in these studies, such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), K-Nearest Neighbour (KNN), Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), Transformer models, and Hybrid CNN-LSTM architecture. Various evaluation metrics such as Accuracy, Precision, Recall, F1-Score, ROC-AUC (Area under the ROC Curve), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were used to measure the performance of the models. Based on this information, each study was reviewed through a comparative analysis. This comparative study helped in understanding how various types of datasets, algorithms, and evaluation methods influence the accuracy of predicting digital burnout. Additionally, an analysis was conducted regarding the most frequently used methods, the advantages of Deep Learning over traditional machine learning, and the effectiveness of multimodal frameworks in detecting digital burnout. Subsequently, a detailed comparative analysis of the selected research studies was conducted. This involved a critical analysis of the strengths and limitations of each study based on key factors such as prediction accuracy, automatic feature extraction, temporal learning, computational complexity, real-time applicability, personalization, interpretability, privacy preservation, scalability, and real workplace validation. Based on this entire study, several significant research gaps have clearly emerged. These include the inadequate integration of behavioural and psychological data, the absence of real-time digital burnout monitoring systems, a lack of models tailored to individual needs, the absence of long-term behavioural analysis, the limited availability of privacy-preserving artificial intelligence systems, and a scarcity of research specifically focused on professionals in the IT sector. Based on the shortcomings identified in this research, a hybrid deep learning framework has been proposed that integrates behavioural and psychological data; it is highly accurate, personalized, privacy aware, and operates in real-time. The findings of this systematic literature review indicate that techniques such as LSTM, CNN, Transformer, and hybrid deep learning architectures have yielded more accurate results than traditional machine learning methods. The primary reason for this is the ability of these models to automatically learn complex behavioural patterns. Multimodal approaches which utilize a combination of behavioural, psychological, and textual data provide a more comprehensive and accurate assessment of digital burnout than methods based on a single source of information. However, this review highlighted a significant need for Explainable AI, real time deployment, privacy preserving frameworks, and validation based on large-scale workplace datasets. Overall, the findings from this systematic literature review provide significant guidance for IT professionals to develop digital burnout detection systems that are more reliable, intelligent, scalable, and practical for real-world use in the future.

Discussion

A review of the literature clearly indicates that digital burnout is an increasingly serious problem in modern workplaces. This issue is particularly prevalent among employees who use computers, mobile phones, and other digital devices for extended periods, those working in work from home or remote environments, and professionals who remain constantly connected to technology. Research by Tarafdar et al. [2], Dragano and Lunau [3], and Tams et al. [4] has shown that excessive technology usage and techno stress negatively impact employees' mental health, productivity, and job satisfaction. These findings indicate that digital burnout is emerging as a significant occupational issue in the modern workplace. Comparative analysis also revealed that deep learning based methods prove to be more effective than traditional machine learning techniques. Research by Chen et al. [18], Wang et al. [24], Iyer et al. [38], and Nair et al. [39] found that LSTM, CNN, and hybrid CNN-LSTM models yielded more accurate results. This is because these models are capable of autonomously learning complex behavioural patterns from users' time-sequenced behavioural data, without requiring any additional manual feature engineering. Consequently, digital burnout can be predicted with greater accuracy. Research by Zhou et al. [26], Singh et al. [27], Park et al. [40], and Das et al. [46] has demonstrated the greater effectiveness of multimodal frameworks. These methods utilize a combination of behavioural, psychological, textual, and physiological data. Consequently, this enables a more comprehensive and accurate assessment of an individual's mental state compared to systems based on only a single type of data. However, these studies have also highlighted certain practical challenges. Key

challenges include the effective synchronization of data from diverse sources, increased computational complexity, the protection of sensitive personal information, and adherence to ethical standards. Due to these obstacles, the large-scale deployment of multimodal burnout detection systems in actual workplaces remains limited. The findings of available research indicate that future research needs to place greater emphasis on developing Explainable AI, personalized burnout prediction systems tailored to individual needs, privacy-preserving frameworks, and real time monitoring systems. Developing effective solutions to these challenges will make digital burnout detection systems more transparent, reliable, and practically applicable in actual workplaces. This research provides a crucial direction for developing more accurate, intelligent, and useful digital burnout detection systems, particularly for professionals in the IT sector.

Conclusion

This systematic literature review clearly demonstrates the growing importance of Artificial Intelligence (AI)-based systems in identifying digital burnout among IT professionals. In particular, techniques such as LSTM, CNN, Transformer, and hybrid deep learning models show significant potential to accurately detect the risk of digital burnout by effectively analysing behavioural data. However, certain significant challenges remain in this field. These include issues such as the protection of personal information (privacy), the need for systems tailored to the individual (personalization), real-time monitoring, and effective deployment in actual workplaces. It is essential to find effective solutions to these challenges. Therefore, it is essential to place greater emphasis on developing digital burnout detection systems that are scalable, ethical, and user-centric. Such systems would enable more effective safeguarding of the mental health of IT professionals, facilitate the timely diagnosis of digital burnout, and make the implementation of appropriate preventive measures easier.

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