



Design and Theoretical Specification of an AI-Enabled Framework for Burnout and Turnover-Intention Risk Assessment in Technology Firms

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Abstract

This design-stage study aims to create and theoretically specify an artificial intelligence (AI)-enabled conceptual framework for assessing burnout risk and turnover intention in technology companies. Previous studies have examined burnout or employee turnover using organisational, psychosocial, behavioural, and AI-based approaches separately; however, limited research has integrated these dimensions into a unified framework. The gap inspires the present study at the design stage, which is a theoretical development of an integrated framework for understanding burnout risk and turnover intention in technology organisations. A priori power analysis was performed, and a sample size of at least 171 participants was determined. The study follows Design Science Research (DSR) methodology for artifact development, supported by bibliometric mapping to identify relevant research trends and theoretical foundations. The results of the bibliometrics helped to select the constructs, integrate them with theories, design questionnaires, and identify gaps in studies. The proposal is based on the models of Bianchi, Maslach and Menezes, consisting of 35 observed items from 5 constructs, which is equal to 28 proposed facets. Its main contribution is the development of a theoretically grounded framework that supports proactive approaches for managing burnout risk and employee turnover intention in technology organisations. The proposed framework may support proactive HR decision-making, while its organisational effectiveness and economic impact, including potential reductions in turnover-related costs, require further evaluation.

Keywords: Burnout, Artificial Intelligence, AI, Predictive Models, Employee Turnover

1. Introduction

Burnout (also called job burnout) is described as an occupational phenomenon that occurs due to chronic work stress that is inadequately managed (WHO, 2024). This is particularly significant because of the increasing presence of this concept in the world of work. A survey with over 5,000 Latin Americans indicated that over 45% had experienced this at least once in 2024 (BUK, 2025). Likewise, a Boston Consulting Group study shows that most workers around the globe at some point in their career have suffered from "burnout," which refers to a condition of being disenchanted from work and feeling unfulfilled. According to a recent BCG report, the average across eight countries is that 48% of workers in these countries are currently experiencing this phenomenon. This is a survey of 11,000 Australian, Canadian, French, German, Indian, Japanese, UK and US office and frontline workers (Boston Consulting Group, 2024).

These statistics are definite and reflect a silent crisis, beyond geographical boundaries and across a range of industrial sectors. This setting places burnout in a broader framework of not only being an individual health issue but one that impacts organisational sustainability and economic productivity. Scientifically speaking, the concept of burnout is well documented as a psychological condition brought about by the effects of chronic work stressors, and the classic model of Maslach and Jackson (1981). The factors or dimensions that lead to burnout (emotional exhaustion, depersonalisation, and low personal accomplishment) have been investigated by these authors. Later, the Labor Demands and Resources (LDR) Model was developed (Bakker et al., 2003; Bakker & Demerouti, 2007; Bajgain, 2025; Alzu'bi et al., 2024). This model outlines the direct and indirect links between work demands, work resources, motivation and work-related stress. Furthermore, this model, in which the aforementioned variables are reciprocally

related, has allowed for a better understanding of their causes, dimensions, and consequences. However, most of these studies have focused on identifying burnout once it is already present, limiting themselves to descriptive or diagnostic measures rather than seeking to predict it early.

According to the research, predictive models with the application of Machine Learning (ML) have been proposed to detect burnout syndrome (Chen et al., 2025; Grządzielewska, 2021; Hernández, 2024). These studies, however, are geographically limited and culturally specific, so they cannot be easily replicated and are more likely to focus on a reactive intervention style, which is not the one that is suggested in this study, but rather a preventive or proactive intervention approach (ALDabbas et al., 2024; Hussein, 2016). These cited studies do not discuss specific organisational factors that affect the work experience: the normalisation of overexertion, a high perception of job insecurity and rigid hierarchical structures.

In Mexico, studies have been conducted to create predictive models for controlling employee turnover in companies (Márquez et al., 2023). However, they do not specify the industry type, nor have they focused solely on operational profiles (Burgos Cruz et al., 2025; Rabeh et al., 2023). Likewise, not all these models use artificial intelligence (Márquez-Hermosillo et al., 2023). There are a few studies that develop early predictive models of burnout, but these are adapted to other sectors, such as healthcare, specifically for traumatologists and orthopedists (Castro-Tamayo et al., 2025; Rubio-López et al., 2025; Al-Housein, 2005; Adisa et al., 2026a), and do not integrate perceptual, behavioural, and organisational variables from an explainable artificial intelligence approach. The aim of this study is to create an AI-enabled framework for early detection of the risk of burnout and turnover intention in technology companies in Mexico (Beyari & Hashem, 2025). The novelty lies in integrating psychological deterioration, organisational conditions, and behavioural outcomes into a unified AI-enabled framework specifically designed for technology organisations. Key contributions of the study are a theoretically integrated model, a context-specific measurement framework and an explainable AI-based early-warning approach to keep employees proactively.

2. Literature Review

In the 1970's, the research psychologist Christina Maslach coined the term burnout, which she described as an expression of chronic stress in a professional setting. The literature has no consensus yet on setting clearly defined diagnostic criteria for the syndrome (Schuch Reimann & Bagatini, 2021). It was recognised as an "occupational phenomenon" in the eleventh revision of the International Statistical Classification of Diseases (ICD-11) in 2019, no longer being seen as a disease (World Health Organization, 2022). Burnout syndrome is specifically defined as a work-related phenomenon in the ICD-11, and is included in Chapter 24 Factors influencing health status or contact with health services. Specifically, it is a problem with employment and unemployment (code QD85) that has a more specific concept of origins in employment (INSST, 2022).

Depression and anxiety are estimated to cost the world one trillion dollars a year in lost productivity (World Health Organization, 2024), or 12 billion working days every year. As a result, 42% of workers globally said that they have suffered from burnout at least once in their working lives (Future Forum, 2023), which highlights the need for organisations to deal with the phenomenon. A key barrier to understanding and tackling burnout is that there isn't a shared diagnostic definition of burnout internationally (Bataineh et al., 2025; Al-Shammari et al., 2023; Adisa et al., 2026b). At least 142 different definitions for the syndrome or scales were found in 182 studies that included 109,628 people in 45 countries from 1991 to 2018. This heterogeneity reflects some significant conceptual disagreement in the current academic literature in this field (Heinemann & Heinemann, 2017; Rotenstein et al., 2018; Vinkers & Schaafsma, 2021; Celestin, 2024). The other facet of the problem with burnout in Latin American countries is not much better. According to a survey conducted by job search platforms such as Bumeran, Laborum, Multitrabajos, and Kozerta, eight out of ten workers in the region report being victims of burnout (79%); in Chile, 82%; in Panama, 78%; in Ecuador, 74%; and in Peru, 66% (Lorena Guarino, 2022). In Argentina, another study by Bumeran revealed that 94% of the workers experience this syndrome (Forbes, 2023; Al Mohazie et al., 2023; El Hussein et al., 2016). The above figures are not only alarming but also serve as a good basis for appreciating the significance of this study, as the subject is now a common occurrence in the world of work and is a problem among a large number of workers worldwide. The economic consequences of this are crippling to organisations and countries (Saleh et al., 2025; Rabeh et al., 2016; Joaquim et al., 2026).

2.1 Mexico

The Mexican labour market has one of the highest employee turnover rates among digital professionals in Latin America. With a rate of 19.2%, it ranks third among economies where employers have the greatest difficulty retaining specialised talent, behind only Argentina (32.4%) and Brazil (19.5%) (Dubost, 2022). Allen and Vardaman (2021) point out that labour costs typically account for 70% of operating expenses and that when employees leave, companies must replace them through human resource management

processes, including recruitment and selection, onboarding, and training (Saleh et al., 2025). These costs represent a significant expense for companies that could be avoided with lower turnover.

In Mexico, 75% of workers also suffer from fatigue, and the stress of work is fairly high. This, however, is less than the China-reported figure of 79% and greater than the U.S. figure of 59% (Lozano Luviano, 2023). Therefore, in the United States, it is estimated that the costs of burnout amount to \$500 billion per year, as well as up to 550 million lost workdays per year due to stress at work, providing relevant comparative context for Mexico (Medina-Dominguez et al., 2023). The five primary causes of the condition were found to be the work itself, personal finances, violence, traffic, and relationship or family issues (IMSS, 2019; Ortiz et al., 2025). The same phenomenon has a great impact on administrative roles; a study conducted in 2023 revealed that over 40% of the respondents felt burnt out (Lozano Luviano, 2023; Ortiz et al., 2025; Subih et al., 2025). The gap has been bridged with the aim of incorporating organisational, psychosocial and behavioural factors within an AI-based burnout framework in this study. It is looking to develop and mathematically test an early-warning artefact, and is bringing a defined measurement tool and new model for technology companies in Latin America.

2.2 Hypotheses Development

Employee turnover is a massive challenge for Human Resources departments and organisations' sustainability around the globe, especially in industries that rely on specialised talent, like tech (Samašonok, 2024). The COVID-19 pandemic and the mass exit (Linzer et al., 2022) of workers from their jobs have made it more challenging for companies to keep and motivate employees (Formica & Sfodera, 2022; Shukla et al., 2022). This phenomenon means that there is always a "war for talent" in the labour market and that there are significant economic and operational losses. There are multiple factors that affect employees to leave their jobs, and among them, burnout and mental health are the major factors that affect their decision to quit their job (Alblihed & Alzghaibi, 2022; Qin et al., 2023). For this reason, research like that of AXA (2025) has identified a close link between mental health and the intention to leave the job, especially with regard to the younger generations (18 – 24 years old), with the factors that determine the exit from the job being very diversified. However, high workloads (52%), salary levels (54%), challenges in achieving work-life balance (51%) and inadequate management styles (48%) have been named as the key factors behind this decision (AXA, 2025; Inakollu, 2025).

In this context, the instrument constructed in this study is intended to study the factors that can raise employees' desire to leave technology companies. We begin with five research hypotheses:

General:

H1: Organisational resources and work-life balance have a significant (and negative) effect on occupational depression, and occupational depression has a significant (and positive) effect on burnout, which leads to staff turnover intention.

Structural hypotheses:

H2: There is a negative and significant effect of organisational resources on occupational depression.

H3: Work-life balance is negatively and significantly related to occupational depression.

H4: Occupational depression is positively associated with burnout.

H5: Burnout mediates the positive relationship between occupational depression and turnover intention.

In the past decade, changes in work organisation models have increased the amount of labor required and changed the nature of the work environment in which people perform their working activity. Shrinking time at work, working remotely, performance stress, and industry instability have led to scenarios where a person's productivity has been consistently raised, thus increasing the tension between personal and professional life (An et al., 2023). In this scenario, a lot of organisational-related aspects like job satisfaction and work-life balance are drastically influenced. Concurrently, the psychosocial conditions, including a perception of the workload and the uncertainty in the global economy, have set a challenging context that affects the psychological health of workers (Berger Ploszaj et al., 2025).

While literature has reported the adverse association between poor working conditions and organisational outcomes (e.g., poorer organisational commitment, higher absenteeism), it still needs to be investigated systematically what organisational, psychosocial and behavioural factors are most likely to yield early warning signs of the risk of burnout. In this sense, it is essential to examine how perceptions of work can mitigate or intensify this risk across different job profiles (Adamopoulos et al., 2025; Inakollu, 2023). This could be measured using an AI-based model, such as the one proposed in this work (Abualigah et al., 2025; El-Kenawy et al., 2025; Kumar et al., 2025).

3. Methods

The Occupational Depression Inventory (ODI) was used, and the occupational-depression construct was informed by the ODI framework (Bianchi et al., 2022). The target population consists of adult workers in technology companies in Mexico, both operational, administrative, and management. Conceptualising occupational depression as a multidimensional construct, the ODI is widely theoretically specified.

Depression in the model is a dependent latent variable, which is explained by the following observable variables: anhedonia, depressed mood, sleep disturbances, fatigue or loss of energy, changes in appetite, feelings of worthlessness, cognitive impairment, psychomotor disturbances, suicidal ideation and intention to leave the company. In this study, different indicators based on the proposed prototype instrument are used, which are based on the ODI framework. The 35-item version is only an adapted version of the original instrument, and the resulting measure should not be viewed as a direct administration of the complete ODI but as an instrument that needs to be theoretically specified empirically.

The three frameworks are integrated because it is theoretically possible that they are in fact three sequential stages of employee risk. Occupational depression is a psychological deterioration that occurs at the beginning, burnout is a psychological deterioration that is accumulated over time, and turnover intention is a behavioural outcome of these psychological deteriorations. Therefore, occupational depression can lead to burnout, and burnout can lead to a higher employee turnover intention. The integration of these viewpoints allows for the linked integration of psychological, occupational and behavioural aspects within the proposed framework in a theoretically structured model.

Later, the prototype's burnout element is based on the conceptual dimensions of the Maslach Burnout Inventory (MBI): emotional exhaustion, depersonalisation, and personal accomplishment (Maslach, 1997). The 35 items on the questionnaire do not represent the full set of items in the MBI, so this is considered an adapted MBI indicator set that needs empirical psychometric validation. This model is considered the international benchmark for measuring the syndrome. In the proposed model, burnout acts as a mediating latent variable, explained by emotional exhaustion, depersonalisation, and personal accomplishment. It proposes that, from a cause and effect point of view, in order to increase the occupational depression level, the burnout phenomenon is likely to also increase; this can be empirically tested using a regression model and SEM.

The dimensions of the turnover intention framework suggested by Ike et al. (2023) are applied to develop indicators of turnover intention. The adapted items are designed to assess withdrawal intentions and perceptions related to the employee's future within the organisation, and their factorial structure and psychometric performance need to be confirmed in the next empirical study. This is conceptualised as a latent, dependent variable, influenced by both burnout and organisational and personal factors: subjective social status, organisational culture, personal orientation, expectations, and professional growth. Integrating these variables allows us to estimate their direct and indirect contribution to the intention to leave. Figure 1 shows the conceptual model of this research.

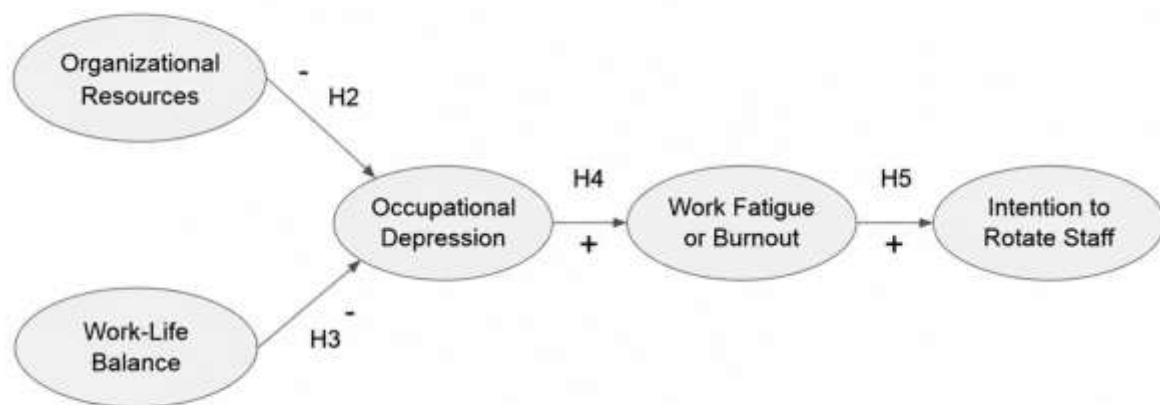


Figure 1. Conceptual model

3.1 Justification of the Methodological Approach

To strengthen the proposal, the Design Science Research (DSR) methodology was used (Peffer et al., 2007). As a design-stage study, AI is considered an enabling perspective that supports the integration and interpretation of burnout and turnover-related factors within the proposed framework rather than an implemented predictive model. This methodology focuses on solving complex organisational problems by designing and evaluating innovative artifacts. It is fundamental for structuring the development of the measurement instrument and the architecture of the predictive framework for the early detection of burnout (burntrack.ai) (Eyadat et al., 2025; Rahi et al., 2026).

Design Science Research (DSR) is used and is located in the artifact design and conceptual evaluation steps. For this reason, the study neither presents empirical results on participants nor validation results of models nor statistics. The outputs of the design phase are the proposed questionnaire, the conceptual relationships, and the burntrack.ai artifact, which will be used for empirical evaluation in a future validation study. This distinction is relevant since the present study provides a framework of theory and methodology for prediction, but cannot prove its predictive accuracy.

The methodological goal is then to provide a clear track from problem identification and a theoretical specification of that problem to the development of an artifact, the operationalisation of its measures, and then a planned empirical evaluation. The next step in the validation process should evaluate the reliability and validity of the measurement, the structural relationships, the predictive power of the measurement, and the generalisability of the measurement with an independent sample from the target population.

The research process has been structured around the following six DSR dimensions:

- 1) The problem identification and motivation: Loss of talent in the technology industry has been identified as one of the major reasons for high operation costs. This research is motivated by the idea of creating a model that will offer an anticipatory, psychological and organisational diagnostic tool to manage burnout.
- 2) Definition of the solution objectives: To design a predictive framework, with a platform that allows integration of psychosocial and organisational variables into a 35-question survey. The goal is for the solution to be applicable and scalable through AI (Chinnaperumal et al., 2025).
- 3) Design and development of the artifact: In this step, both the burntrack.ai measurement instrument and the conceptual model were developed. The design is based on the standardisation of three theoretical constructs (ODI, MBI, and TSI) and specific organisational resources, resulting in 28 study dimensions comprising 35 questions. These are governed by the cause-and-effect logic supporting the hypothesis that organisational resources and work-life balance are significant predictors of burnout and, therefore, of employee turnover.
- 4) Demonstration: The artifact is demonstrated by the proposal of the conceptual model (Figure 1), and the experimentation protocol proposes a logical structure in which the hypothesis establishes that the levels of occupational depression and burnout can be measured to predict or manage early staff turnover.
- 5) Evaluation (Design Phase): Evaluation is theoretical with respect to the coherence of the design, consistency of the constructs with proposed indicators, and consistency of the research problem, hypotheses, measurement architecture, and the predictive objective. The claims of reliability, construct validity, predictive accuracy, classification performance, and generalisability are not made because participant-level validation data were not obtained during this design phase. Empirical evaluation is a study in which the instrument and the predictive model will be tested on an independent sample that is reserved for a further study.
- 6) Output knowledge: This article contributes to a comprehensive model and theoretically sound measurement instrument for the scientific community and the organisations, which can offer organisations a strong instrument for proactive management of burnout. This study has paved the way for further research to quantify the instrument and to add to empirical knowledge about the predictive accuracy of the instrument.

3.2 Calculation of the proposed sample size

Sample size was calculated a priori with the possibility of statistical power analysis using the G*Power 3.1 software. It was considered a multivariable regression model with 15 predictors, with a moderate effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$ and a statistical power of 0.80. Based on the analysis, the number of participants needed was determined to be at least 171.

The assumed maximum structure of the predictors ($n = 15$) does not mean that the number of questionnaire items is 15 or the number of conceptual dimensions is 15. The observed indicators given by the 35 items of the questionnaire are represented by the variables of the proposed model. This distinction prevents the identification of measurement indicators with structural predictors.

This article is a design stage study; thus, the calculated value of 171 is not the value that was achieved in the present research, but is treated as a minimum value for future empirical research. Future validation studies should also take into account the possibility of attrition, missing responses, model complexity, and the need for the final statistical learning process when setting the recruitment goal. Figure 2 shows the G*Power process.

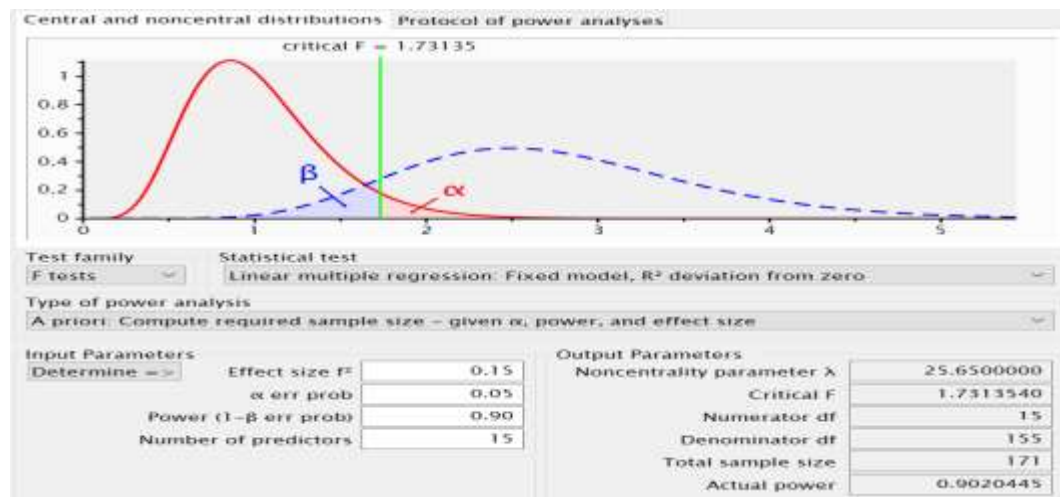


Figure 2. G*Power

Figure 3 displays the G*Power result of a sample size of 171 participants.

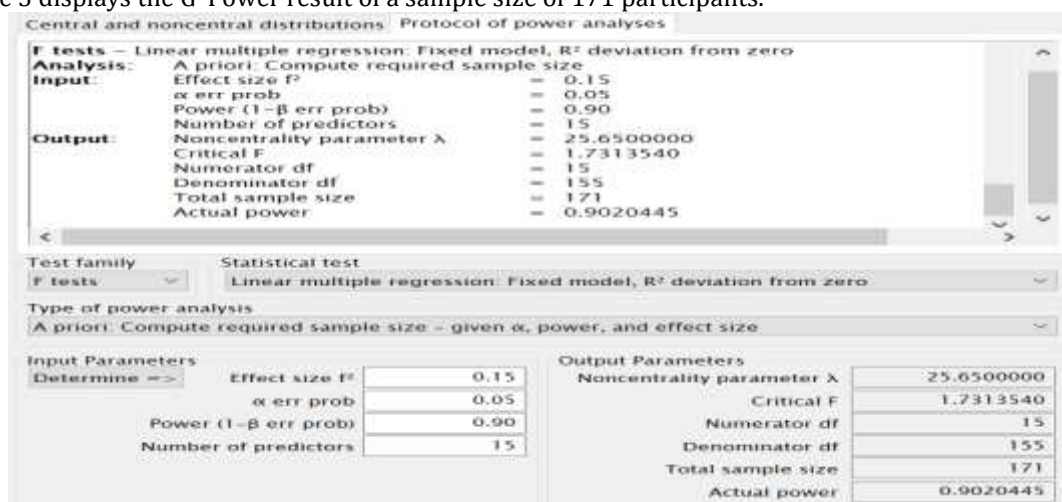


Figure 3. G*Power result

3.3 Analysis Techniques

3.3.1 Bibliometric Analysis

For this study, a bibliometric analysis was performed using the Biblioshiny tool, obtaining information from the SCOPUS database; a total of 16,552 documents were reviewed, from the period of 2021 to 2026, 1421 sources, 4291 authors, where the average age of the documentation is 2.1 years, which indicates how recent this research is. Other research sources external to SCOPUS were also used, mainly information obtained from world and governmental organisations in Mexico. Table 1 shows the search string and the corresponding information for the filters used in SCOPUS.

To ensure the reproducibility of the bibliometric procedure, four steps were considered, i.e., database retrieval, eligibility control and filtering, bibliographic data preparation, and descriptive bibliometric analysis. The choice of SCOPUS as the main bibliographic database was made due to the fact that it covers a wide range of disciplines and has structured metadata. The search was limited to papers that were indexed from 2021–2026, and further narrowed by document type, subject area, and language as defined in Table 1. The bibliometric outputs were created after the records were retrieved from the search strategy and were screened based on the following criteria. The last set of data was then analysed with Biblioshiny to detect trends in the publications, distribution of sources, productivity of authors, and scientific production of countries.

To create the intellectual and publication environment for the proposed research, rather than to give empirical support for the predictive relationships in the conceptual model, the bibliometric analysis is used. Hence, the significance of bibliometric results in terms of research development and thematic relevance is interpreted, but not in terms of validation of a proposed burnout prediction framework.

Table 1. SCOPUS search strategy and eligibility filters

Search string	Year range	Languages	Limited to	Limited to
TITLE-ABS-KEY (Burnout OR "quiet quitting" OR "Inteligencia Artificial" OR "Artificial Intelligence" OR "A.I." OR "Modelos predictivos" OR "Predictive Models" OR "Predictive Model" OR "Justicia Organisational" OR "Organisational Justice" OR "Rotación de personal" OR "Employee Turnover" OR "Employee Churn") AND Publication period: 2021–2026 (PUBYEAR > 2020 AND PUBYEAR < 2027) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (LANGUAGE, "English") OR LIMIT-TO (LANGUAGE, "Spanish"))	2021–2026	English-Spanish	Business, Administration and Accounting	Items only

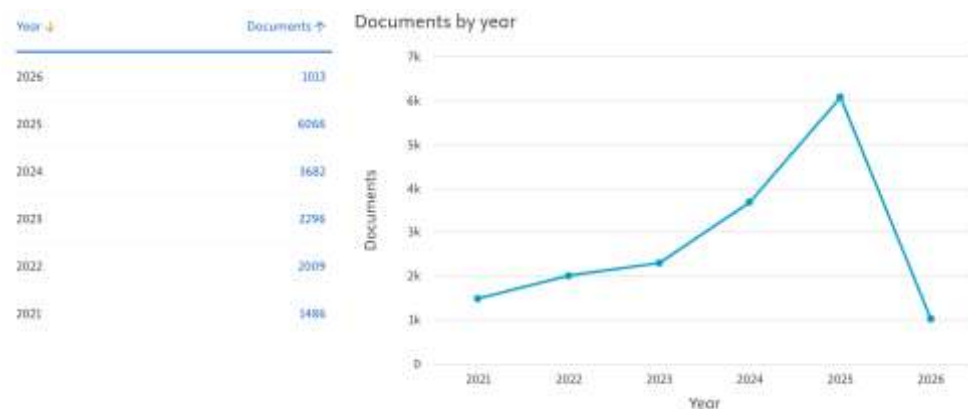


Figure 4. Document by year analysis

In Figure 4, it can be observed that annual production almost doubled from 2024 to 2025, underscoring the relevance of our research topic and its worldwide importance.

Table 2. Output by country

Country	Freq
CHINA	8851
USA	7295
INDIA	4733
UK	2617
GERMANY	1812
AUSTRALIA	1698
ITALY	1573
SPAIN	1338
SOUTH KOREA	1212
FRANCE	1176

Table 2 shows the 10 countries with the highest scientific output in our research topic, with the top three being China (8851 documents), the United States (7295), and India (4733). It is concerning that no Latin American country appears in the top 10 for research output.

3.4 Design of questionnaires or experimental protocols

To support both our general hypothesis and the four structural hypotheses, a questionnaire was designed that covers the five constructs: organisational resources, work-life balance, occupational depression, burnout, and turnover intention, as well as the 28 dimensions, as we can see in the following table:

Table 3. Constructs and dimensions

Construct	Dimensions
Organisational Resources: (Internal Structural Factor)	1) Material/structural resources 2) Social resources 3) Control resources 4) Motivational resources 5) Cognitive structural resources
Work-life balance: (external structural factor)	6) Psychological disconnection 7) Work-life conflict (low level) 8) Organisational culture of boundaries 9) Border control 10) Techno-invasion (low)
Occupational depression	11) Anhedonia 12) Depressed mood 13) Sleep disturbances 14) Fatigue/loss of energy 15) Changes in appetite 16) Feelings of uselessness 17) Cognitive impairment 18) Psychomotor disorders 19) Suicidal ideation 20) Intention to staff turnover
Burnout	21) Emotional Exhaustion 22) Personal Fulfilment 23) Depersonalisation
Burnout and Turnover intention	24) Subjective social status 25) Organisational culture 26) Personal guidance 27) Expectation 28) Professional growth

The mapping in Table 3 should be viewed as a starting point, not an endpoint, for creating a psychometric measurement model. In the prototype scale of 35 items, there are a number of dimensions that are represented by one indicator. Therefore, it is not possible to obtain the dimension-level internal consistency and latent-construct reliability with only the current design. An empirical phase should test the dimensional structure and the need for other indicators for constructs that are proposed for latent-variable modelling. A 66-question questionnaire was first created, which was divided into five major constructs and 28 specific dimensions. Later, it was reduced to 35 questions according to cognitive load theory by Clark & Kimmons (2023). According to this theory, working memory is a limited resource in humans. In respect of surveys, the mind of a person gets fatigued if there are more than 30 or 40 complex questions on the questionnaire. In order to prevent this phenomenon, the method mentioned above was used, and only the most important questions were considered for the primary objective of the study.

The item reduction was not seen as a psychometric validation process but more as an instrument development process. Items were kept on the basis of their conceptual fit with the five target constructs, extent of coverage of the proposed dimensions, clarity of item wording, and relevance for the technology-sector content. The 35-item version is thus a prototype instrument that is parsimonious. The item set must be expertly content-theoretically specified and piloted before it is empirically deployed to see if the indicators selected for each construct are representative and if there are any items that need to be modified, dropped, or expanded.

3.5 Planned Empirical Validation

The next empirical part will be followed in a step-by-step approach. The questionnaire will be reviewed by experts to ensure that the content is relevant, clear, and covers the constructs, and then tested with a small group of participants (pilot test) to find out which items are not clear or effective. Second, the data from the entire sample, used to validate the instrument, will be examined for any missing items, any problems with the quality of responses, distributional properties and common method bias. Third, the properties of the measures will be examined using relevant factor-analytic techniques, such as internal consistency, convergent and discriminant validity, and factor structure. Last, the hypothesised structural relationships will be tested by employing an appropriate framework of multivariable modelling. Yet, out-of-sample evaluation of predictive performance will be conducted that will not only be based on in-sample fit, but also on suitable performance measures depending on the final operationalisation of the outcome, either as a continuous risk score or as a categorical risk classification. This methodical process will provide the empirical evidence that will help to establish if the proposed artefact performs as designed.

4. Design Outputs and Bibliometric Findings

In the design and development stage of the DSR methodology, we have been able to integrate three basic outcomes of the Talent Management process:

The artifact, burntrack.ai: A high-fidelity prototype, which translates theoretical constructs into a prescriptive solution, has been created. The system can be operated as a conceptual decision-support artifact for risk indicators and provides a conceptual foundation for developing an operational tool for early intervention (Khan et al., 2025).

The instrument of the questionnaire consists of 35 items, which have been designed as an instrument to cover some proposed constructs, but reduce the length of the questionnaire for the respondents. The psychometric properties of the scale, such as reliability, convergent, discriminant, and factor structure, have yet to be theoretically specified through empirical research. Adapting the instrument to the local context ensures its relevance to the technology sector and covers the five key concepts in a balanced way.

Bibliometric results: In the analysis of 16,552 documents, it is observed that the scientific production on Burnout and AI has increased exponentially from 2024 to 2025. There is a crucial lack of research from Latin America, however, which substantiates this study and makes it a required reference for the region.

The bibliometric results were also used for the development of the frameworks. Patterns of keywords identified recurring themes relating to emotional exhaustion, organisational resources, burnout, artificial intelligence and predictive analytics. The dimensions of burnout, organisational resources, and the ability to predict burnout using AI were identified in the suggested framework and supported by these themes. Hence, the analysis not only provided evidence of research relevance but also a foundation for determining constructs of importance.

5. Discussion

The integration of three models (Bianchi, 2022) (occupational depression), (Maslach, 1997) (burnout), and (Menezes, 2018) (Turnover) on a multidisciplinary approach provides a comprehensive view that has not yet been covered by the HR literature. This theoretical amalgam suggests a new causal sequence between worsening mental health and the loss of talent, in which burnout acts as a crossway between them. The model thus is no longer just a technical description, but a proper theoretical foundation to explain turnover in the technology sector.

In this context, the model's applicability is specifically targeted to urban ecosystems that are technological hubs and "digital clusters", with a high level of competition in the labor market, like Guadalajara, Mexico City, Monterrey, Bogotá or São Paulo. In these highly dynamic environments, traditional Human Resources management often fails to detect changes in employee well-being in time due to the speed of market transformations (Inakollu, 2022). However, not an exhaustive list; an AI-powered model could offer a potential tool for recognising patterns that could be linked to increased burnout risk, provided it is empirically and theoretically specified, achieves the correct level of model performance, and is responsibly implemented within the organisation (Raju et al., 2025; Naz et al., 2025).

In this regard, the use of explainable AI in the model is a theoretical paradigm shift in human capital management; from reactive management based on diagnoses once the problem is no longer reversible, to prescriptive and preventative management of workplace well-being. This can be a preventive bridge where AI transforms workplace-detected psychological symptoms to clear and human-centric strategic management actions based on real-time data (Hamasha et al., 2025).

In addition, reducing the number of items from 66 to 35 is a key technique in cognitive load management for data collection to ensure the theoretical validity of the collected data. If the constructs being measured

are to be accurately captured in response, then participant fatigue is important in high-pressure corporate environments for ensuring that the predictive framework is robust and the information gathered for HR decision-making is of high quality.

In terms of contributions and limitations, the primary contribution is the artefact architecture, which is theoretically informed and connects the painstakingly collected organisational, psychosocial, burnout, and turnover-related data together into a proposed framework of early warning: design knowledge. The model is positioned as a robust and scalable tool that connects psychosocial symptoms with talent retention strategies, offering a solution that reduces operational costs associated with turnover and prioritises employee well-being. However, it is acknowledged that the main limitation lies in the need for empirical validation in samples of more than 171 participants, as well as the importance of considering cross-cultural variability in future iterations.

Three limitations are methodologically highlighted. Firstly, this study is still in the design phase and thus cannot be used as empirical evidence of the accuracy of the predictions. Secondly, the proposed instrument consists of 35 items, and the indicator structure is very short, so it is difficult to guarantee multidimensional construct reliability without further psychometric testing. Third, the bibliometric evidence is sourced primarily from the SCOPUS database, and therefore is limited to the coverage and indexing of this database. The limitations do not detract from the design contribution, but rather set boundaries for the conclusions that can be validly drawn from the present study.

In addition to empirically applying the proposed model to technology companies, future lines of research could draw on comparative studies across other industries, such as manufacturing and services, two of the main productive sectors worldwide.

It should also look at segmentation by employee type (operational, administrative, managerial) and include qualitative methods to complement the quantitative approach and gain a deeper understanding of the results, such as focus groups or in-depth interviews with specific types or profiles. This research would not only be useful to the scientific field of human resources, but it would also be beneficial to the field of employee mental health. The resulting information can then be leveraged to enhance current public policies with recommendations for new workplace mental health guidelines and more stringent measures.

6. Conclusions

The purpose of this research is to create a theory that can be used to identify the early signs of burnout and the possible link between the occurrence of such and an employee's intention to quit their job. Using the Design Science Research (DSR) methodology, the artifact burntrack.ai was developed, which theoretically demonstrates that it is feasible to manage talent proactively rather than reactively, with mental health as a fundamental factor, thereby ensuring employee job retention in organisations. The study presents evidence that the risk of work-related burnout does not just occur, but is a multicausal process and one that is iterative, being strongly shaped by the lack of organisational resources and the continued imbalance between personal and professional life. The strength of the originality and principal theoretical contribution is the integration of three internationally specified constructs the Occupational Depression Inventory, the Maslach Burnout Inventory and the Turnover Intention Scale that have been described separately.

Furthermore, the framework is designed for technology development hubs in Latin America, where software and digital services are found, and its transferability needs to be compared in an empirical way across these contexts. The pressure to hire talent and the needs of digital productivity create a heightened need to have precise measures to lessen the burden of these factors on mental health in cities designated as technology hubs. In terms of the application of the research, a structured prototype of items for future empirical data collection in the technology sector is given, consisting of 35 items. Implementing this predictive system provides HR departments with early warning, facilitating more humane strategic interventions to reduce the high financial costs associated with the turnover of skilled personnel and to prevent labor lawsuits arising from inadequate workplace conditions. The major restriction is that the artifact and measurement tool have yet to be tested empirically. The value of 171 is the minimum number of samples that were calculated according to the power-analysis assumptions, and is not meant to be used as a threshold for future validations. In future research, it is recommended to investigate other sectors of industry and to expand the segmentation of the different types of professional roles, e.g. managers, administrative, and operating workers, by other qualitative methods.

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