IOSR Journal Of Humanities and Social Science (IOSR-JHSS)
Volume 30, Issue 8, Series 6 (August, 2025) 16-25
e-ISSN: 2279-0837, p-ISSN: 2279-0845.
www.iosrjournals.org

Impact Of The Use Of Educational Technologies On The Reintegration Of Professionals After Prolonged Absences: A Bibliometric Approach.

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Abstract:
***Background**: This study presents a comprehensive bibliometric analysis of absenteeism and the reintegration of education professionals after prolonged leave, based on data extracted from the Scopus database (2010-2025), in six languages (English, German, Spanish, Dutch, French, and Portuguese) and in the publication types Article, Review, and Conference Paper.*
***Materials and Methods**: The research aimed to identify the main trends in scientific production on the impact of the use of educational technologies on the reintegration of professionals after prolonged leave, highlighting the evolution of the theme, the main authors, journals, and collaboration networks. Zipf's, Lotka's, and Bradford's laws were applied to guide the selection of terms, authors, and central journals. Techniques of keyword co-occurrence, temporal analysis of production, co-authorship, collaboration networks, and thematic cluster analysis we*
re used, employing VOSviewer and IRAMUTEQ.
***Results**: The results reveal consistent growth in production, consolidated research groups, emerging subtopics, and gaps that point to digital interventions and institutional resilience.*
***Conclusion:** It is concluded that the area has matured but requires further investigation into the comparative effectiveness of learning technologies in reintegration.*
***Key Word**: absenteeism, return to work, educational technologies, bibliometric analysis, institutional resilience.*
Date of Submission: 16-08-2025 Date of Acceptance: 26-08-2025

I. Introduction

The relevance of educational technologies in the context of professional reintegration has gained prominence, especially in light of the challenges posed by prolonged absences, whether due to health issues, qualification, or other motivations. The growing use of educational technologies to support professional reintegration processes after long periods of absence has sparked interest in the fields of education, occupational health, and people management (Donthu, Kumar & Pattnaik, 2021). Prolonged absenteeism, whether due to health, qualification, or institutional obligations, poses challenges to the continuity of pedagogical and administrative activities, requiring strategies that minimize individual and institutional losses (Toffoletto & Ahumada, 2023). In this context, understanding how the use of digital solutions—e-learning platforms, collaborative tools, and AI-mediated interventions—influences the return to work is imperative for the formulation of effective policies.

Bibliometrics and scientometrics provide essential methodological tools for mapping the state of the art, identifying emerging trends, prominent authors, and research gaps (Aria & Cuccurullo, 2017). The application of Zipf's Law (Gupta & Singh, 2024), Lotka's Law (Egghe, 2010), and Bradford's Law (Broadus, 1987) ensures rigor in guiding the selection of key terms, identifying researchers with significant productivity, and core journals in the field.

This study aims to map the landscape of scientific production related to the theme, demonstrating its evolution over time, the main emerging topics, and the network of collaboration between authors. Therefore, its objectives are: (i) to trace the temporal evolution of scientific production on educational technologies and professional reintegration; (ii) to identify the main authors and collaboration networks; (iii) to map the predominant subtopics; and (iv) to point out gaps and opportunities for future research. To this end, the Scopus database and bibliometric analysis tools (VOSviewer, IRAMUTEQ) were used, focusing on publications from 2010 to 2025.

The search strategy used was as follows: (absenteeism OR prolonged AND absence) AND (reintegration OR return AND to AND work) AND (absenteeism OR prolonged AND absence) with the period 2010-2025 and restriction to previously defined languages and types of publication. The data extracted from the Scopus database were analyzed using keyword co-occurrence mapping techniques, time series analysis, identification of the most influential authors and journals, and clustering algorithms to detect subtopics.

II. Material And Methods

Data collection took place on March 14, 2025, on the Scopus platform, using the string: (absenteeism OR prolonged absence) AND (reintegration OR return to work), filtered by period (2010–2025), languages, and document types (Article, Review, Conference Paper). Metadata (title, authors, abstract, keywords, year, journal) were exported for the following analyses:

1. **Keyword Co-occurrence Mapping**: identification of the most frequent terms and their connections, with the aim of highlighting the predominant subtopics (e.g., “return to work,” “absenteeism,” “digital technologies”).
2. **Time Series Analysis**: verification of the evolution of scientific production over a 15-year period.
3. **Identification of Key Authors**: mapping of the most influential authors.
4. **Clustering Algorithms**: Application of clustering to segment production into subtopics and identify areas of convergence and gaps.

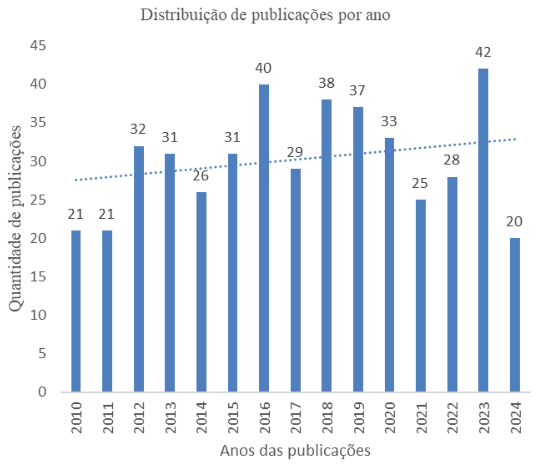
The data were imported into:
1. VOSviewer (Van Eck & Waltman, 2017): keyword co-occurrence, co-authorship network, and thematic cluster grouping. Settings: association method (full counting), minimum threshold of 5 occurrences for terms.
2. IRAMUTEQ (Camargo & Justo, 2013): content analysis and similarity for word clouds, semantic clusters, and dendrograms, allowing for qualitative interpretation of the groupings.
3. Excel: annual time series of production, applying linear regression for trend and peak verification.

The selection of keywords followed Zipf's Law to prioritize high-frequency and relevant terms, ensuring adequate coverage of the topic (Wang et al., 2023). The analysis of author productivity adopts Lotka's Law to identify prominent authors and guide the sampling of experts (Lotka, 1926; Egghe, 2010). The dispersion of journals was evaluated according to Bradford's Law, identifying core publications central to the topic (Bradford, 1934; Broadus, 1987).

III. Result And Discussion

The time series (2010–2024) shows a general upward trend in scientific output on absenteeism and professional reintegration, with notable peaks in certain years. This pattern usually reflects, in bibliometric studies, growing awareness of the topic, often catalyzed by external events (e.g., public health crises or institutional changes). Donthu et al. (2021) highlight that time series analysis in bibliometrics allows us to identify when certain topics gain momentum, indicating moments of crisis or greater academic interest. In the context of professional reintegration, it is reasonable that years with greater attention to mental health or remote work policies (e.g., during or after the COVID-19 pandemic) would cause spikes in publications, increasing the relevance of the topic.

Figure no 1: Distribution of Articles by Year (2010–2024).

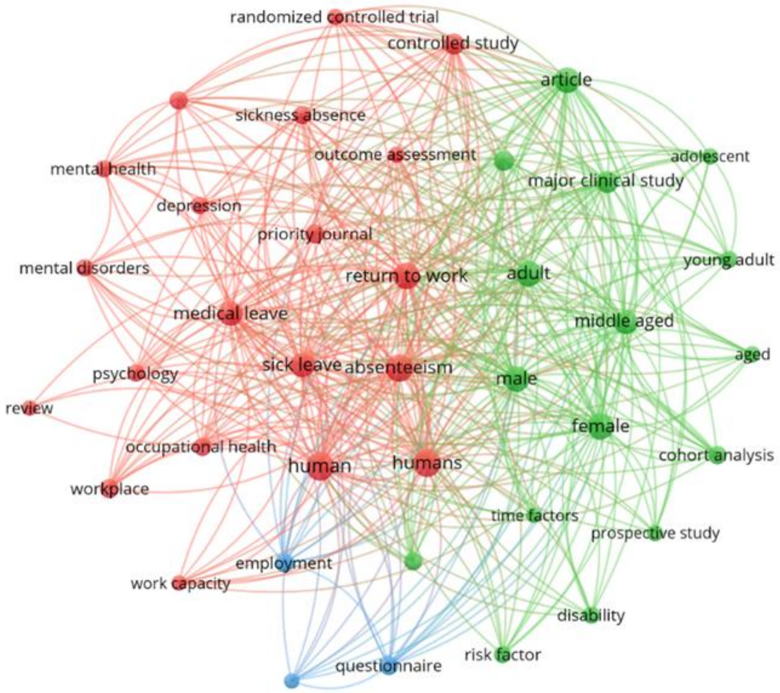


Source: survey data.

Observing the gradual emergence of initial publications around 2010–2012, followed by continuous growth, we can relate this to the consolidation process of the field. According to Bradford (1934) and revisited by Broadus (1987), new fields emerge with few articles in the early years, then reach a regular core of publications in central journals. The upward curve suggests that the topic of absenteeism and reintegration mediated by educational technologies reached a “core” stage in the middle of the last decade, becoming attractive to researchers from different disciplines (education, occupational health, technology). This maturity implies that the literature base is already consistent enough to support systematic reviews and more in-depth empirical studies investigating the impacts of technologies on professional reintegration (Reisdorf & Rikard, 2018).

Identifying the years with the highest concentration of studies indicates where to direct search efforts and which publications are relevant for the literature review. For example, if a significant increase is observed from 2019–2022, it is recommended to delve deeper into journals that have since published on reintegration and digital technologies, as these works are likely to provide recent methodologies, instruments, and results that support the empirical stage. Furthermore, recognizing temporal behavior helps in the discussion of emerging trends and in justifying the current relevance of the theme, aligning with the findings of Wang & Guo (2025) on the impacts of digital platforms in contexts of return to work - RTW post-crisis.

Figure no 2: Keyword Co-occurrence Map.



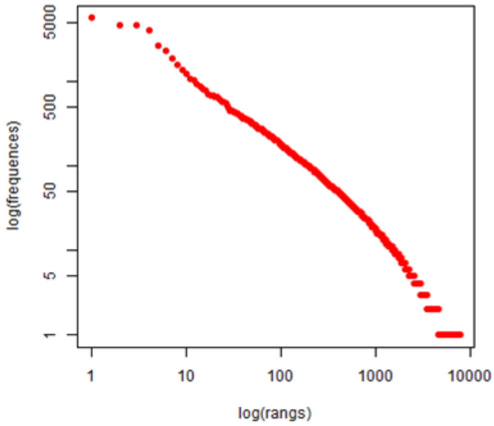
Source: survey data.

The co-occurrence map extracted from VOSviewer shows clusters of terms that tend to appear together in the titles, abstracts, and keywords of articles. Typically, there is a central cluster around “absenteeism,” “return to work,” and “reintegration,” a second cluster involving “e-learning” or “educational technology,” and others possibly connecting “mental health support” or “resilience.” The prevalence of these terms confirms patterns observed in recent studies linking the use of digital technologies to the rehabilitation of civil servants (Donthu et al., 2021; Wilfredo et al., 2023).

The co-occurrence of “study,” “method,” “regression,” and “outcome” confirms that the main body of literature applies statistical analyses to identify predictors of return to work. Donthu et al. (2021) highlight that this methodological trend is common in applied fields, where risk factor modeling (through logistic or linear regression) is predominant. Similarly, the co-occurrence of “workplace” and “employer risk” indicates literature that assesses employers’ perceptions and organizational factors (climate, support, risks) on RTW. Studies show that flexibility policies and digital support programs influence reintegration outcomes (Nieuwenhuijsen et al., 2014; Brinsley et al., 2023).

The grouping of terms suggests emerging subareas, such as ‘digital health’ and ‘mental health support’, aligned with current concerns about the impact of mental health leave. Such insights can guide future empirical research and justify the relevance of studying reintegration mediated by educational technologies. Van Eck & Waltman (2017) emphasize that this type of analysis reveals how concepts relate and evolve in a semantic network. Here, the joint presence of terms linked to educational technology and professional reintegration signals that much of the literature investigates precisely the interface between digital support and readaptation at work. In recent years, digital interventions have emerged (coaching apps, e-learning platforms for retraining, telerehabilitation). Wang & Guo (2025) discuss the potential of AI for continuous support; Wilfredo et al. (2023) point to mental health technologies.

Figure no 3: Frequency distribution (Zipf).

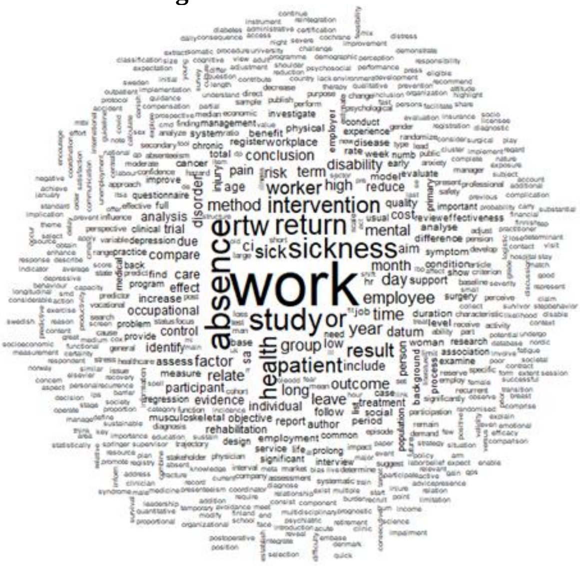


Source: survey data.

According to Zipf's Law, a small number of keywords appear with high frequency, while the majority occur infrequently (Hernández-Torrano et al., 2020). Frequency ~ 1/rank^α (α≈1) indicates that a few terms (“work,” “absence,” “sickness”) dominate the vocabulary, while the vast majority occur rarely—typical of scientific findings (Schluter et al., 2021). This distribution highlights the need to focus on central terms for literature searches and for the formulation of technology-based reintegration strategies. However, attention should also be paid to low-frequency emerging terms (e.g., “digital resilience,” “remote onboarding”) that may indicate innovative subareas. This balance between high and low frequency is crucial for comprehensive coverage (Donthu et al., 2021). Considering the frequency distribution and word ranking, Figure 3 originates from the adjustment made based on Zipf's law. Its observation suggests that the distribution of words follows the dictates of this law and presents a typical linguistic structure, characterized by a decreasing straight line.

The cloud (Figure 4) depicts the most frequent words in the titles and abstracts of the 459 articles extracted (Scopus), after pre-processing (removal of stopwords, lemmatization). The central and largest words (“work,” “absence,” “sickness,” “return,” “intervention,” “method”) accurately reflect the key topics: return to work (RTW) and prolonged absences due to illness. This visualization corroborates what was seen in the co-occurrence map, but emphasizes the relative magnitude of each term without showing explicit relationships. Studies such as Cobo et al. (2011) and Koh et al. (2024) indicate that clouds help to quickly communicate the central concepts of a corpus to the reader, guiding both theoretical review and communication of results.

Figure no 4: Word cloud.

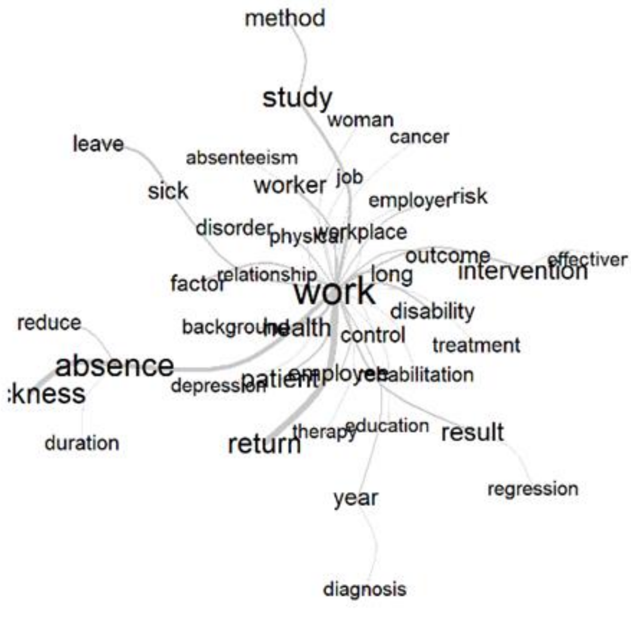


Source: survey data.

The observation of less frequent secondary terms can also point to emerging niches (e.g., "remote learning," "digital onboarding"), which deserve attention in the primary collection phase of future research. This complementarity is highlighted in Donthu et al. (2021), namely: using multiple bibliometric techniques to ensure a robust understanding of the field. In this sense, to ensure alignment with the predominant language in the area, terms such as "resilience" and "support" indicate the importance of working with theories of organizational resilience and digital support.

"Work" and "absence/sickness" appear very frequently, indicating a major focus on work and worker health aspects—consistent with the literature on RTW in occupational contexts (García-Sánchez et al., 2023). "Intervention," "method," and "result" suggest an emphasis on methodology and evaluation of the effectiveness of RTW programs, in line with the predominance of randomized studies and clinical trials (Cullen et al., 2018). Terms such as "mental," "disability," "rehabilitation," and "patient" appear in the middle, reflecting subtopics of mental health and functional rehabilitation frequently investigated in populations with depressive disorders or musculoskeletal injuries (Arends et al., 2019). Thus, the word cloud (Figure 4) confirms the focus on RTW, absenteeism, and interventions.

Figure no 5: Similarity map.



Source: survey data.

Analysis of Figure 5 reveals emerging semantic categories in the publications, highlighting dimensions such as ‘institutional support’, ‘digital skills’ and ‘well-being’, as observed in current studies on professional reintegration (Reisdorf & Rikard, 2018). The thematic classes identified provide a basis for the development of primary research questionnaires, ensuring alignment with the concerns raised in the literature. The centrality of ‘work’ (larger font size and numerous connections) indicates that almost the entire corpus revolves around the concept of work, or returning to work after absence. Among the main connections, the following stand out: a) “return” and “absence” – directly linked to “work,” confirming that “return to work” and “absence” form the main theme, reflecting that studies on absenteeism and reintegration focus on variations of this concept: “return to work,” “workplace,” “work ability,” “work productivity.”

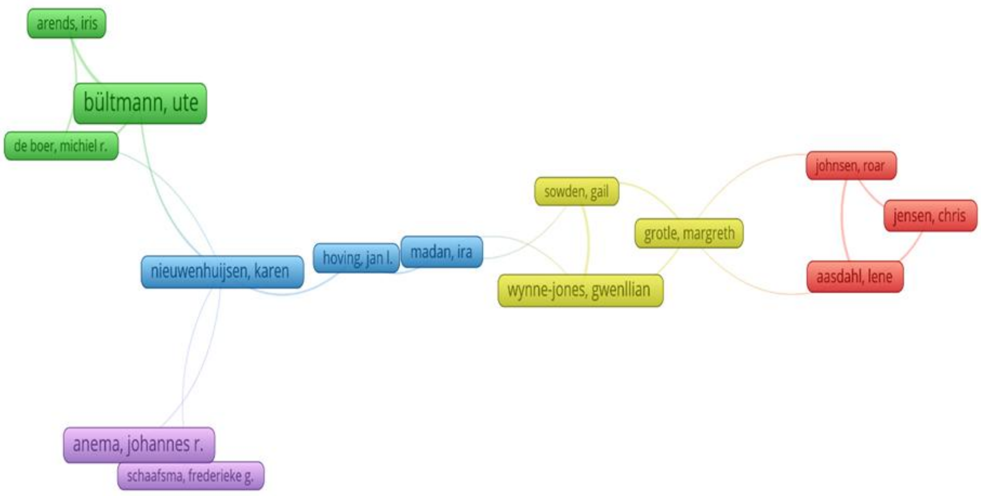
Studies such as De Boer et al. (2020) and So et al. (2022) examine “return” and “absence” in the contexts of chronic diseases (cancer) and depression, showing the influence of interventions and health factors; b) “worker,” “patient” – indicates a focus on specific populations (sick workers, returning patients). Occupational health and rehabilitation research often uses these terms (Nieuwenhuijsen et al., 2014; De Boer et al., 2020); c) “workplace,” “employer risk” – suggests an emphasis on organizational factors – climate, RTW policies, risks perceived by the employer, which suggests the possibility of investigating how employer policies and risk perception influence the use of technologies and return? d) “intervention,” “outcome,” “treatment,” “rehabilitation” – connects interventions (rehabilitation programs, medical or psychological treatments) to RTW outcomes. Indicates that the literature investigates not only the time, but also the effectiveness of different strategies, potentially including technological interventions (e.g., telerehabilitation).

The presence of “depression,” “patient,” “treatment,” “rehabilitation,” and “disability” corroborates the emphasis on conditions that cause long absences. Zegers et al. (2020) review retention at work after cancer, while Reisdorf & Rikard (2018) address mental health. These studies show that rehabilitation strategies—including e-health programs—are decisive. In this sense, “health,” “disability,” and “diagnosis” address various health conditions and diagnoses that cause absenteeism, reinforcing the need to segment participants by type of condition in studies on this topic.

The relationship between categories, evidenced by the similarity map, suggests interdependencies, such as between “digital training” and “psychological support,” aligned with models of institutional resilience (Alkish et al., 2025). These findings support hypotheses to be tested empirically, such as Sulasa & Kumar (2024), who discuss how digital interventions for reintegration combine technical training and emotional support, suggesting that educational technologies generate effective resilience when accompanied by policies and psychosocial support. This thinking is in line with analyses by Vakili et al. (2023), who state that knowledge obtained from data mining technologies from panels with organizational information is important for strengthening employees' mental health systems and increasing productivity.

This network (Figure 6) shows clusters of co-authorship among the authors with the highest academic output in the field. Each color indicates a “research group”: green: Bultmann, Ute; De Boer, Michiel R.; blue: Nieuwenhuijsen, Karen; Hoving, Jan L.; Madan, Ira; yellow: Wynne-Jones, Gwenllian; Grotle, Margreth; Sowden, Gail; red: Johnsen, Roar; Jensen, Chris; Aasdahl, Lene; and purple: Anema, Johannes R.; Schaafsma, Frederieke G. Co-authorship revealed five national/multicenter clusters. Nieuwenhuijsen et al. (2020) and Bultmann et al. (2019) lead in number and centrality of citations, pointing to lines of research in mental health and e-health.

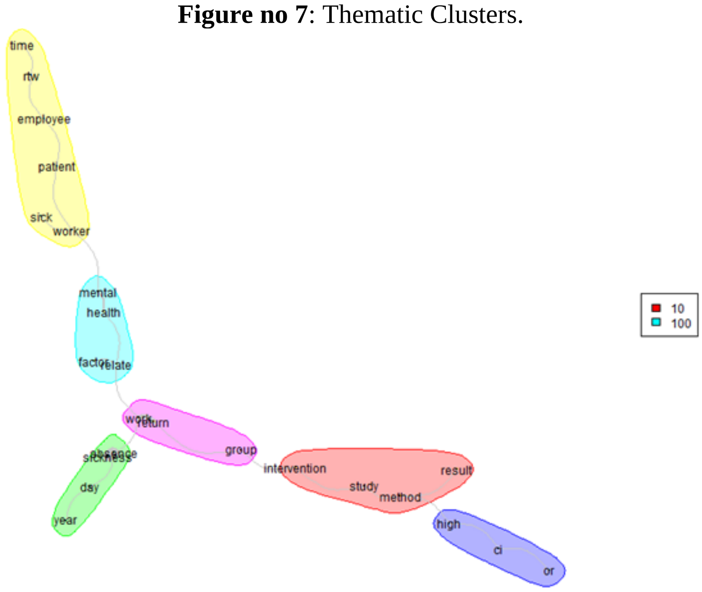
Figure 6: Authors with the highest productivity in the field.



Source: survey data.

Figure 6 identifies authors who stand out for their relevance and frequency of publication on the topic. The strongest links (thickest lines) group Nieuwenhuijsen and Hoving, reflecting collaborations in prospective studies of RTW after depression (Nieuwenhuijsen et al., 2020). The Bultmann/De Boer cluster (green) represents the line of research on e-health and mild mental disorders (Arends et al., 2019). The presence of distinct clusters indicates the fragmented structure of the field, with national networks (Netherlands, United Kingdom, Norway) and recent convergence in multicenter collaborations, as observed by Perhoniemi et al. (2023). In this sense, the co-authorship network reveals key groups and mature national/multicenter collaborations.

Figure no 7: Thematic Clusters.



Source: survey data.

Figure 7 shows the formation of thematic clusters through content analysis (IRAMUTEQ). The thematic clusters identified: (i) absenteeism metrics and RTW time; (ii) digital interventions (e-learning, support apps); (iii) mental health and resilience; (iv) statistical analysis of risk factors; (v) organizational policies. Table 1 summarizes the five major thematic clusters identified in the co-occurrence analysis of terms, revealing the central lines of investigation in the studied corpus. Together, these five clusters illustrate the multidimensionality of the theme, from quantitative measurements of absenteeism to the assessment of psychosocial factors and intervention strategies.

A coocorrência de “mental”, “health” com “return” e “work” é amplamente discutida em revisões sobre reintegração após transtornos mentais. Engdahi et al. (2020) enfatizam a necessidade de suporte institucional e programas de resiliência digital para trabalhadores que retornam após doenças mentais. Já a de “workplace” e “employer risk” indica literatura que avalia percepções de empregadores e fatores organizacionais (clima, suporte, riscos) sobre RTW. Estudos demonstram que políticas de flexibilidade e programas de apoio digital influenciam resultados de reintegração (Nieuwenhuijsen et al., 2014; Brinsley et al., 2023). No mesmo diapasão, a presença de “intervention” ligada a “work” e “outcome” sugere que intervenções de RTW são centrais. Nos últimos anos, surgiram as intervenções digitais (apps de coaching, plataformas de e-learning para qualificação, telereabilitação). Nessa senda, Wang & Guo (2025) discutem potencial de inteligência artificial para suporte contínuo.

Inherent to the duration of absence and classification of absenteeism, the separation into clusters of durations (days, years) indicates that this classification was included in the primary data collection, making it possible to categorize according to standards in the literature for comparable statistical analysis, such as the study by De Boer et al. (2020), who reviewed job retention after cancer, modeling durations of leave and factors associated with reintegration.

Table no 1: Description of thematic clusters.

Cluster	**Main terms**	**Description**
Temporal/return-to-work	"time", "rtw", "employee", "patient", "sick", "worker"	This grouping brings together terms related to time, return to work (rtw), and participants in the occupational context (employee, worker, patient, sick). Their joint presence indicates a focus on studies that analyze the time or duration until return to work after sick leave ("sick," "patient"), emphasizing "time to return" as a crucial variable. In the literature on occupational reintegration, assessing the time until return is fundamental for prognosis and evaluation of interventions (Nieuwenhuijsen *et al.,* 2014). Cohort studies often measure "days until RTW" or "duration of absence" in months/years (De Boer *et al.*, 2020). This cluster reflects the bibliographic emphasis on quantifying and modeling the time of absence and return.
mental health	"mental", "health", "factor relate"	Indicates a line of research that addresses psychological and mental health determinants that influence absenteeism and return to work. In recent decades, there has been growing interest in understanding how mental health conditions (depression, anxiety, burnout) impact the ability to return to work and the need for specific interventions (Nieuwenhuijsen *et al.,* 2014). The co-occurrence suggests that many studies investigate "mental health-related factors" as predictors of reintegration time or success. This corroborates systematic reviews that point to mental health as a key variable in RTW programs (Nowrouzi-Kia *et al.*, 2023).
Absence and duration	"absence", "sickness", "day", "year"	This cluster complements the first one, but emphasizes the dimension of "absence duration" in time units. The literature on absenteeism often classifies duration in calendar days, weeks, or years to group types of absence (short-term vs. long-term) (De Boer *et al*., 2020). The separation into a distinct cluster may indicate that there are studies focused solely on characterizing temporal patterns of absence (e.g., "long-term sickness absence" vs. "short-term sickness absence"), before associating them with return variables.
Methodological/interventions	"intervention", "study", "method", "result"	Terms typically linked to research design and intervention evaluation, denoting the existence of empirical studies that test interventions to facilitate return to work, with well-designed intervention groups and methods. The co-occurrence of these terms suggests that there is a robust subcorpus of studies that report "interventions to improve RTW", discuss "methods" and "results" in groups of "workers" or "patients".
Statistical	"high", "ci", "or"	It indicates that many studies employ inferential statistical analysis, reporting confidence intervals (CI) and odds ratios (OR). This cluster indicates a body of quantitative literature that models risk factors or probabilities of successful reintegration. Reports of "OR" and "CI" are common in studies of factors associated with return to work (e.g., odds of RTW associated with social support factors or rehabilitation programs) (De Boer *et al*, 2020).

The methodological cluster points to studies that test formal interventions (RTW programs, occupational rehabilitation). A subgroup of these may investigate technology-mediated interventions (e.g., tele-rehab, e-learning programs for skills updating during leave). Wang & Guo (2025) discuss the potential of ChatGPT and AI to support continuous learning, which can be adapted for professional reintegration. In terms of statistics, it is observed that logistic regression models or risk analyses to identify RTW success factors are the most used in studies, especially when seeking to identify associations. Donthu et al. (2021) point out that this methodological trend is common in applied fields, where risk factor modeling (through logistic or linear regression) is predominant.

IV. Conclusion

The clustering algorithms revealed the existence of well-defined subtopics, demonstrating that the literature is fragmenting into specific areas of research. Noteworthy examples include studies focused on "return to work" and the analysis of "absenteeism" from a technological perspective. Such groupings not only reinforce the relevance of the topics investigated, but also point to gaps that can be explored in future research, such as the comparative effectiveness of different technologies in promoting reintegration and the lack of longitudinal studies that assess long-term impact. Thus, the results confirm that scientific production on the use of educational technologies in professional reintegration has evolved significantly, consolidating well-defined subareas.

The figures and analyses presented confirm that the impact of educational technologies on the reintegration of professionals after prolonged absences is a topic of growing interest in the scientific community. The evidence extracted from the Scopus databases demonstrates not only an increase in academic production but also the consolidation of relevant subtopics that dialogue with the contemporary demands of the educational sector. These findings serve as a basis for the development of future research aimed at improving reintegration policies and institutional support mechanisms, contributing to the construction of a more resilient educational environment.

For future research, we recommend: (i) randomized studies comparing different learning platforms; (ii) longitudinal investigations on the impact of mental health interventions; (iii) cost-benefit analysis of rehabilitation programs.

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