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Human-centric process improvement through digital transformation: contributions and limitations

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Abstract

Paper aims: This study investigates integrating digital transformation, human factors, business process management, and emerging technologies to improve organisational efficiency and employee well-being. The research aims to develop a conceptual model that optimises digital processes while reducing the cognitive load on employees.

Originality: The research fills a gap in the literature by emphasising the intersection of human factors and digital transformation. It introduces a human-centric approach that balances operational efficiency with employee well-being, which has been underexplored in previous studies.

Research method: A systematic literature review was conducted using Scopus and Web of Science databases to identify relevant studies. Content analysis was used to extract criteria for each domain, and Structural Equation Modelling (SEM) was applied to analyse complex relationships between digital transformation and human factors.

Main findings: The results indicate that integrating digital tools into organisational processes optimises workflows and decision-making while mitigating cognitive overload. The proposed model prioritises employee engagement, usability, and well-being alongside technological advancement.

Implications for theory and practice: This study contributes to the theoretical understanding of digital transformation by integrating human factors. The findings provide a structured pathway for organisations to enhance operational efficiency while safeguarding employee well-being, offering a balanced approach to digitalisation that can be applied in real-world scenarios.

Keywords

Digital transformation. Business process management. Human factors. Structural equation modelling.

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Conflict of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Statement
The authors declare that this research did not require ethical approval as it did not involve any experiments on humans or animals.

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1. Introduction

Digital Transformation (DT) can be conceptualised as enhancing an organisation by establishing significant changes in its attributes through the combination of information technology, computing, communication, and connectivity (Vial, 2019). This approach is grounded in various technologies and procedures designed to create more efficient value for customers and businesses (Margiono, 2021).

DT refers to integrating digital technologies and business processes in a digital economy (Yoshikawa et al., 2020), and it has influenced the world of work. As companies adopt digital technologies and automatise procedures, employees face alterations in their usual patterns and duties. These technologies can be simultaneously constructive and detrimental to personnel and their cognitive abilities (Autor, 2015). Overall, technology continues redefining the employment landscape in complex ways. Lower-skilled roles may become obsolete and require retraining, but new domains and high-level jobs emerge (Autor, 2015). Adaptability will be crucial as digital progress shapes future occupations and the daily work experience evolves. Societal support networks can help smooth this transition while empowering humans to focus energies on tasks best suited for human skills and perspectives. Moreover, low job control was more aversive regarding the psychological well-being of technologically fast workers than technologically slow workers (Westerman et al., 2014). In this way, the loss of control oversteps automated by machines seemed to have a more intensive effect than low control (Stapel et al., 2019).

Some examples of negative impacts of DT for workers include information overload and multitasking, where DT can lead to increasing quantities of information for workers to manage and process. Constant digital connection and the pressure for multitasking may cause cognitive overload, stress, and decreased productivity (Richter et al., 2016). Another potential impact is associated with an accelerated pace of work, in which the digitisation of processes often increases efficiency and speed in operations. Additionally, digitising processes may lead to an accelerated work pace with shorter deadlines and urgent demands. The worker may need to produce more in less time, resulting in burnout and exhaustion (Demerouti et al., 2019). The work step accelerates with digitisation, including fast responses and agile decision-making. This scenario may enhance the cognitive load of the worker, leading to stress and mental fatigue (Demerouti et al., 2019).

These examples highlight how Digital Transformation can increase workers' cognitive load due to information overload, multitasking, pressure, and other factors. Therefore, organisations must recognise these challenges and implement appropriate strategies to manage cognitive load, creating a balanced and healthy work environment for employees (Organization for Economic Co-Operation and Development, 2019).

As recent literature identifies, there are significant gaps in understanding how integrating human factors and knowledge management practices in Industry 4.0 can help mitigate cognitive challenges while supporting organisational transformation (Ribeiro et al., 2024). These gaps include a lack of studies on the competencies workers need to adapt to these technological changes in facilitating knowledge retention amidst rapid technological advances (Ribeiro et al., 2024).

In this context, considering the scenario of human factors in the workplace and the ongoing adoption of technologies to achieve the digital transformation of a company, the research problem explored in this study is: "*How can Digital Transformation and its Emerging Technologies improve efficiency in organisational management while minimising cognitive impacts on employees in companies?*".

Based on this guideline, this research identifies the complex relationships with the indicators of DT, human factors (HFE) impacts and Business Processes Management (BPM) to guide the design of an integrated model for Organizational Digital Transformation. This model will provide valuable guidance to organisations, offering insights for the strategic development of organisational capabilities that align with the dynamic nature of the digital transformation process, aiding data-driven decision-making, and educating workers' cognitive load and interpretation errors.

To analyse the relationships among the indicators, we used Structural Equation Modelling (SEM), a multivariate technique increasingly utilised in scientific inquiries to examine and assess complex causal relationships. Distinguished from other modelling methodologies, SEM evaluates both direct and indirect effects within pre-established causal frameworks. SEM has evolved through three generations, with roots tracing back a century, underscoring its enduring relevance and methodological advancements (Hair et al., 2021).

The paper is structured as follows: Section 2 addresses the problem statement regarding human factors' impacts in the workplace. Section 3 presents a literature review and the SEM method. Section 4 is devoted to the application of the SEM. Section 5 discusses the main results and existing gaps in related works. Finally, section 6 concludes and presents perspectives for the research continuation.

2. Theoretical contributions

This study advances the theoretical discourse on Digital Transformation (DT) by integrating the principles of Human Factors and Ergonomics (HFE) into the broader framework of Business Process Management (BPM). By doing so, it addresses a critical gap in the existing literature that often prioritises DT's technological and operational aspects while overlooking the cognitive and psychological implications for employees. Our research provides a structured approach that reconciles technological efficiency with human well-being, offering a balanced perspective on digitalisation.

The primary theoretical contribution of this study lies in developing an integrated conceptual model that links DT, HFE, and BPM. Unlike prior studies that treat these domains separately, our model highlights the interdependencies between digital adoption, cognitive workload, and organisational performance. By applying Structural Equation Modelling (SEM), this research empirically substantiates the causal relationships among these constructs, enhancing the understanding of how digital interventions can be optimised to reduce cognitive strain while improving decision-making and operational outcomes.

Furthermore, this study extends existing theories on cognitive load and automation by demonstrating how emerging technologies influence job control and employee well-being. Prior research has identified that low job control exacerbates the adverse psychological effects of digital acceleration (Westerman et al., 2014; Stapel et al., 2019). Our findings refine this understanding by incorporating human-centric design principles into digital workflows, suggesting that well-structured digital environments can mitigate stress and enhance cognitive adaptability.

From a methodological perspective, this study contributes to the literature by employing SEM to analyse the complex, multidimensional relationships between DT, HFE, and BPM. While SEM has been widely used in management sciences, its application in exploring the cognitive dimensions of DT remains limited. By leveraging this technique, we provide a nuanced and statistically robust analysis of how digital transformation strategies can be designed to enhance both efficiency and employee well-being.

In conclusion, this study enriches the theoretical landscape of DT by bridging the gap between technological advancements and human factors. It underscores the necessity of a human-centric approach in digital transformation initiatives, paving the way for future research to explore more adaptive and cognitively sustainable organisational models. These insights contribute to academic discussions and provide practical implications for organisations seeking to balance digital innovation with workforce sustainability.

3. Methodology

3.1. Systematic literature review protocol

Tranfield et al. (2003) proposed that three steps are necessary for the literature review planning stage: identifying research issues and opportunities, preparing a proposal, and developing a review protocol. For the literature review, four steps are required: definition of the systematic review (keywords and search terms); filters and resulting articles; evaluation and selection of articles; and data extraction.

3.1.1. Research issues and opportunity

The authors propose conducting a scoping study to assess the literature's relevance and size and delimit the subject area or topic. For this purpose, a scoping study was conducted on the four pillars of this review, which are aligned with the research objective: (i) digital transformation, (ii) industry 4.0, (iii) business process management (BPM), (iv) emergent technologies, and (v) ergonomics/human factors (HFE). An isolated search for each term was performed in the Scopus database to identify related terms and define the research keywords. Each area's relevant terms and keywords were identified in the article's title, abstracts, and keywords sections. A similarity analysis was used to count and classify them according to their appearance frequency. The most frequent terms in the articles, the most relevant terms to each research area, were selected as the search keywords for the next step, as shown in Table 1.

Table 1. Selected keywords for systematic literature review survey.

Digital Transformation/ Industry 4.0	Business Process Management	Emergent Technologies	Ergonomics/ Human Factors
Digitalisation	Business Process Improvement	Artificial Intelligence	Human-Computer Interaction (HCI)
Process Automation		IoT	Usability
Digital Twin			Industry 5.0

3.1.2. Preparation of a proposal for a review

Based on the previous step and the research objective, the focus of this systematic review was identified, and the following guiding questions were outlined:

- "*Which articles address emerging technologies in management processes focusing on Digital Transformation?*"
- "*Is there a framework/method/model/approach for applying emerging technologies in management processes? Do any of them consider human factors?*"
- "*Which prominent authors and journals have published on the topic?*"

3.1.3. Development of a review protocol

A review protocol was developed to obtain the answers to the guiding questions. This protocol contains information about the study's specific questions, the search strategy to identify relevant studies, and the criteria for inclusion and exclusion of studies in the review.

Initially, a search was conducted in the Scopus and Web of Science databases using the following equation, considering only the main terms: *("Digital Transformation" OR "Industry 4.0") AND ("Business Process Management") AND ("Emergent Technologies") AND ("Ergonomics" OR "Human Factors").* This search returned no results. Subsequently, the search was revised to include related keywords as well: *("Digital Transformation" OR "Industry 4.0" OR "Digitalization" OR "Process Automation" OR "Digital Twin") AND ("Business Process Management" OR "Business Process Improvement") AND ("Emergent Technologies" OR "IoT" OR "Artificial Intelligence") AND ("Ergonomics" OR "Human Factors" OR "Human-Computer Interaction" OR "Usability" OR "Industry 5.0").* As a result, two articles were found.

Subsequently, the four pillars of the research were related by considering all keywords, first in trios and then in pairs. The correct relationship between the keywords ensures that more satisfactory results are achieved while searching for scientific literature related to the study topic, which also contributes to optimising the literature selection process.

Inclusion and exclusion criteria were defined based on the research questions and the general characteristics of the articles found during the identification stage. The application of inclusion criteria selects articles from the pool gathered in the identification stage with characteristics that might address the research questions. On the other hand, exclusion criteria are used to eliminate works that do not cover relevant issues for the study or are duplicates. The articles that meet all the inclusion criteria are selected for further analysis. The inclusion and exclusion criteria were applied to the article's title, abstract, and keyword sections. The requirements are presented in Table 2.

Table 2. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
✓ English papers	✗ Duplicated papers
✓ Full-text available papers	✗ Non-English papers
✓ Last ten years (>2012 until now)	✗ < 2012 papers
✓ Digital Transformation/ I4.0 keywords	✗ Does not approach Digital Transformation, Industry 4.0 or BPM
✓ BPM keywords	

3.1.4. Definition of the systematic review

The systematic search began with identifying keywords and search terms built from the scoping study. A comprehensive and unbiased search was conducted using the search equations generated based on the keyword's relationship.

The chosen databases for the research were Scopus and Web of Science. The selection of the Scopus database is justified because it is considered the largest multidisciplinary database of abstracts, citations, and full-text scientific literature worldwide, launched by Elsevier in 2004 (Grácio & Oliveira, 2012).

3.1.5. Filters and resulting articles

The results based on the search equation produced a comprehensive list of articles for the review. Filters were applied progressively, and each step's results were recorded and presented in Figure 1.

The initial searches in the Scopus and Web of Science databases yielded 13195 and 11958 articles, respectively. Then, for both cases, the "articles" filter was applied, as it was a bibliographic search, narrowing down the results

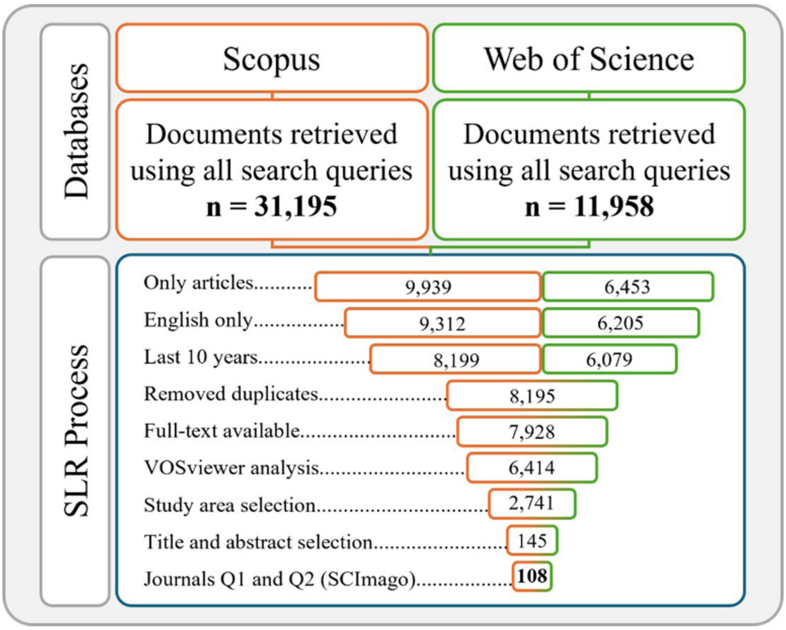

Figure 1. Steps/filters for selecting articles.

to 9939 and 6453 articles. The second filter used was the language filter, selecting only articles in English to ensure broader results, which led to 9312 and 6205 articles. Then, a temporal filter was applied, where only articles from the last ten years were selected, resulting in 8199 and 6079 articles, respectively.

After that, the articles were added to the Mendeley software, and the duplicates were removed from the base. Finally, the "full article" filter was applied, returning only articles published in their final stage, resulting in 7928 articles.

3.1.6. Evaluation and selection of articles

To begin the selection of relevant articles, they were analysed using the VOS Viewer software, which allowed the creation of a keyword network based on the keywords found in the articles, shown in Figure 2.

All the keywords were identified and filtered based on their alignment with the research scope. Consequently, specific articles were excluded from the sample due to their lack of adherence to the defined inclusion criteria (e.g., words such as hydrogel, breast cancer, and ophthalmology were excluded). This selection narrowed down the results to 6,414 articles.

From the initial 6,414 articles, a thorough evaluation was conducted based on the titles and abstracts of each study. New inclusion and exclusion criteria were established for this selection, and only articles that met all the defined inclusion criteria were considered. The defined criteria were as follows:

- Addressing one of the areas of this research in the title or abstract.
- Discussing the application or proposal of a framework/method/model/approach in the theme.

As a result, only studies that fulfilled both inclusion criteria were incorporated into the review, resulting in a total of 145 articles for evaluation and selection based on full-text reading. Before the full-text reading, a pre-selection based on journal classification was performed, including only Q1 and Q2 journals according to the Scimago Journal Rankings (SJR) scale. Sengers et al. (2016) recommend using frequently cited bibliographies and newspapers with a high impact factor to obtain a high-quality review. Therefore, 108 articles were retained for full-text reading and extracting relevant data for this research after this selection process.

3.1.7. Data extraction

Data extraction from the 108 articles was conducted in a custom database using Microsoft Excel® software. The extracted information was divided into two parts: a) article characteristics, including publication year, authors, journal, and keywords, and b) information related to the research variables and outcomes, such as the degree of alignment of the article with the research themes (DT, I4.0, BPM, and Technologies). Following the data classification and analysis, only articles that align with the main themes will be chosen as relevant for this research.

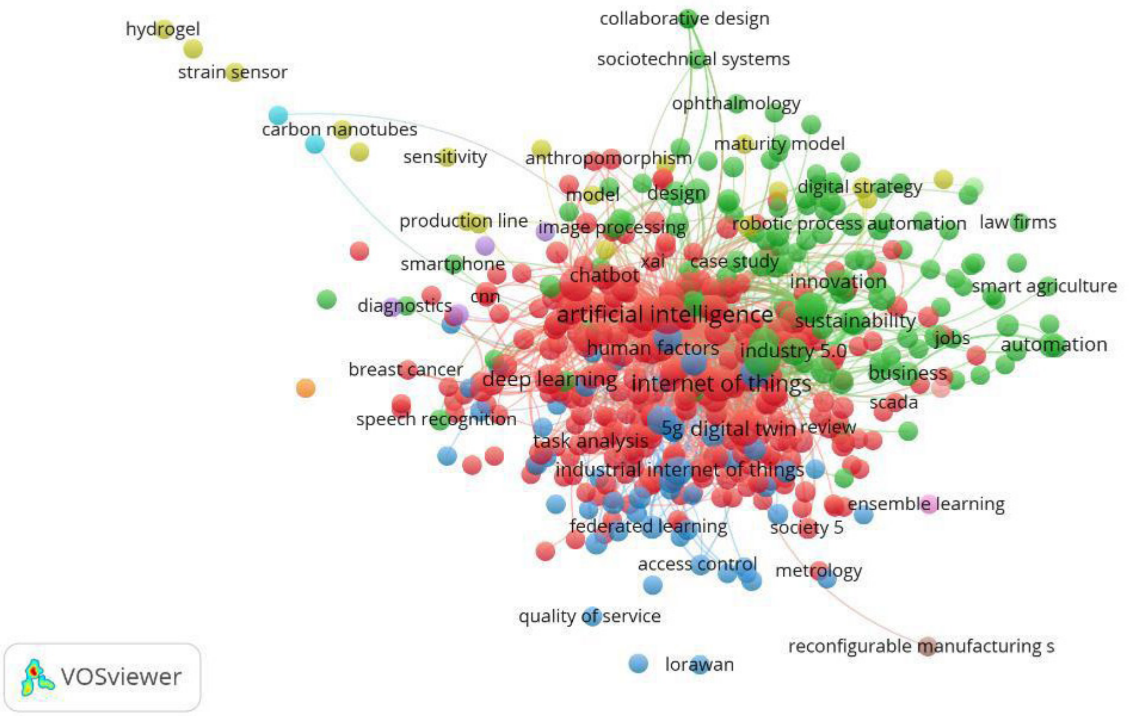

Figure 2. Keywords network analysis.

3.1.8. Bibliometric and content analysis

The Bibliometric and Content Analysis were performed based on the reading, interpretation, and comprehension of the selected research in the Systematic Literature Review. Initially, the articles' characteristics, such as publication countries, authors, journals, and more, were examined. This analysis was based on completing the 108 previously selected articles. The bibliometric analysis aims to explore the authors, the year of publication, the keywords, and the journals. From the 108 identified articles about the most productive authors in the literature, as illustrated in Figure 3, 15 authors wrote more than one article, while another 307 authors contributed only one.

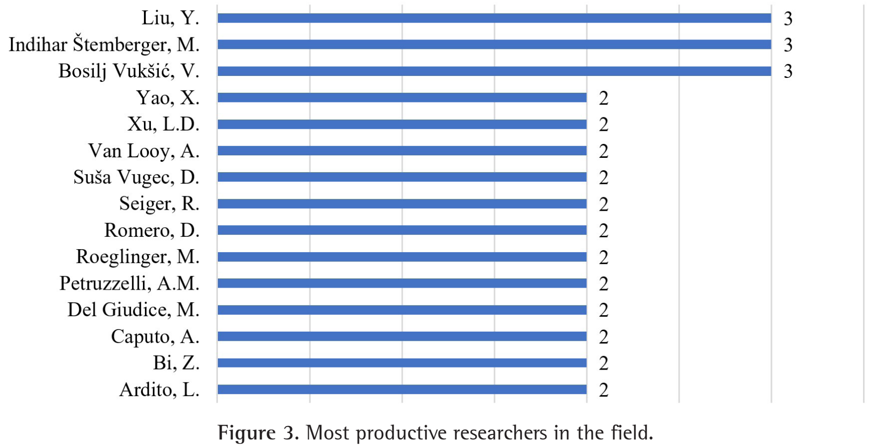

Figure 3. Most productive researchers in the field.

Our findings on research productivity indicate that at least 74% of the articles were published during the past five years. These numbers indicate the research trend in these topics and show that research productivity increased from 2018 onward (see Figure 4). The most frequent keywords among the articles are shown in the word cloud in Figure 5. The most used keywords in the articles were "Industry 4.0", "Artificial Intelligence", "Digital Transformation", "Internet of Things", "Business Process", "Digitalization", and "Human-Computer Interaction".

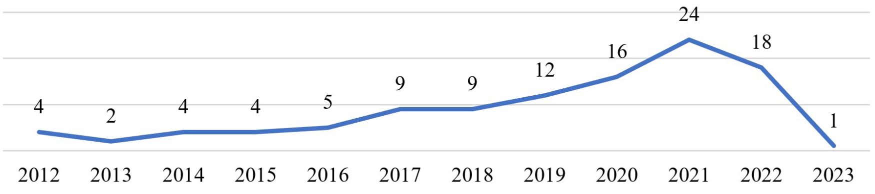

Figure 4. Distribution of publications per year.

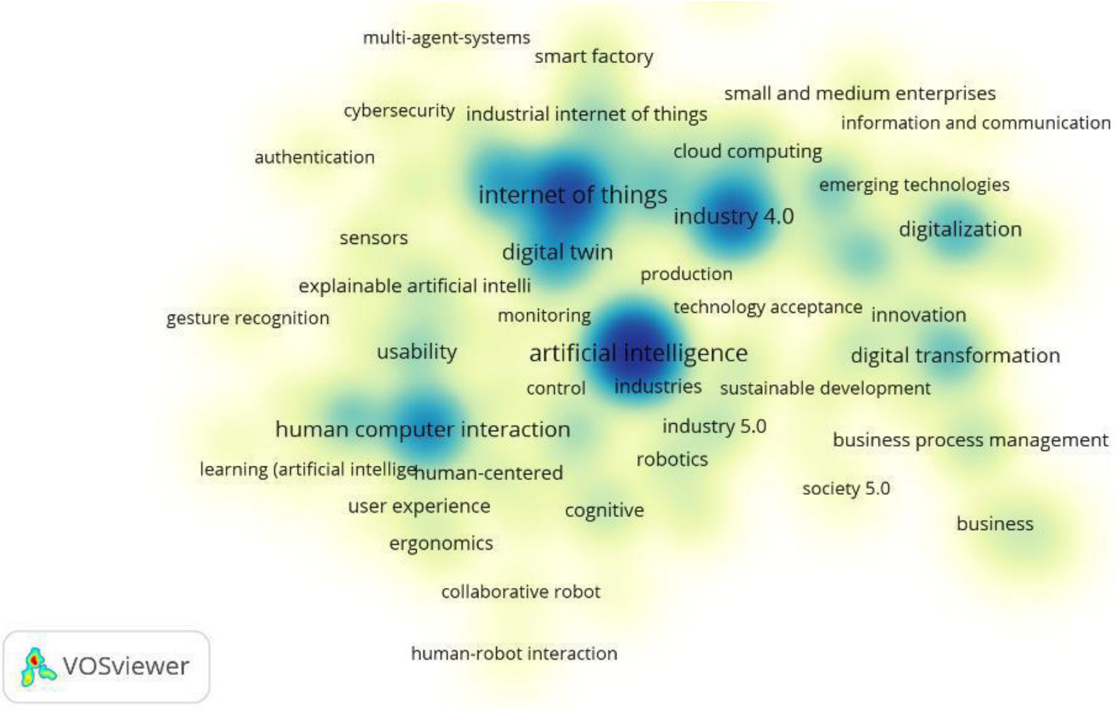

Figure 5. Most used keywords.

In addition, it is essential to analyse that 108 articles are distributed in 52 different journals, of which two journals receive relevant attention: Business Process Management Journal and Sustainability (see Figure 6). Only 11 journals had more than 1 article, and the other 41 journals had one each.

Next, content analysis was conducted. So, the purposes of each research were observed, and the contributions and limitations of each article were listed. The limitations showed existing gaps in the theme. They provided an opportunity to propose a preliminary model to support Digital Transformation in the administrative processes of companies using emerging technologies while considering the cognitive impacts on workers.

As shown in the database search, no articles were found that simultaneously addressed all four domains of this research. Therefore, a classification of the selected articles (108 articles) was conducted to investigate their correlations and limitations based on three criteria: (i) multiple domains, (ii) application and evaluation of the article's proposal, and (iii) human factors considered. The requirements were defined through a literature review combined with the research objectives and problems, identifying the most relevant parameters for categorising the articles.

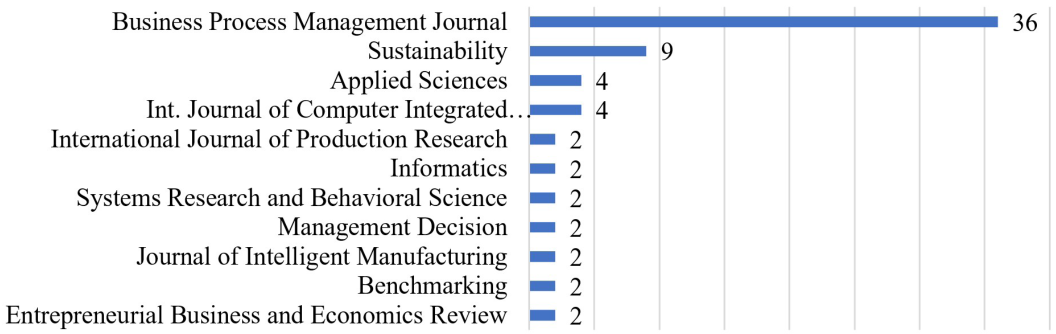

Figure 6. Prominent journals in the field.

The primary objective of this classification was to evaluate the relationships between the areas of study, considering the multiple domains addressed by the articles. Subsequently, we analysed whether the articles proposed frameworks, methods, or models focused on how digital transformation and its technologies can contribute to organisational efficiency while considering the potential impacts these technologies may have on company workers. Lastly, we examined whether the effects of human factors were addressed in these articles. The evaluation results are presented in Table 3.

Table 3. Evaluation results.

Multiple Domains			Application			Human Factors		
MD1	MD2	MD3	A1	A2	A3	HF1	HF2	HF3
86.11%	13.89%	0.00%	83.33%	9.26%	7.41%	82.41%	10.19%	7.41%

The criterion of Multiple Domains (MD) was divided into three subclasses:

i. (MD1) Weak – Articles limited to two specific domains.

ii. (MD2) Moderate – Articles limited to three specific domains.

iii. (MD3) Strong – Articles addressing all four research domains.

The criterion of Application (A) was divided into three subclasses:

i. (A1) Weak – Articles that did not detail the application and results of the proposal.

ii. (A2) Moderate – Articles that detailed the proposal's application but did not evaluate or validate it.

iii. (A3) Strong – Articles that applied and evaluated or validated the proposal.

Lastly, the criterion of Human Factors (HF) evaluated in more detail whether the articles presented human factors issues and was divided into three subclasses:

i. (HF1) Weak – Articles that did not consider human factors.

ii. (HF2) Moderate – Articles that considered human factors.

iii. (HF3) Strong – Articles considering human factors, including cognitive/organisational factors.

Based on these data, it was observed that there are some underexplored issues in multiple domains, specifically in items (MD2) and especially (MD3), and in the application and evaluation of proposals in items (A2) and (A3). Regarding multiple domains, none of the articles addressed all four areas of this research, and only 13.89% considered three of them. Concerning application, most articles did not present an application or case study of the framework or approach proposed in the article; 9.26% presented a practical application example without evaluating or validating the proposal, and 7.41% offered some type of proposal evaluation. Lastly, 10.19% considered human factors, and only 7.41% specifically considered cognitive/organisational factors.

Thus, according to the classification conducted, only 15 articles were identified as highly relevant to this research, essential as a scientific basis for the present study. To summarise, after analysing the selected articles, the results of SLR showed that adopting Digital Transformation is no longer a prolonged choice. It has become a necessity for businesses to succeed in the market. However, while reading the articles, a wealth of information was revealed about how adopting new technologies and digital transformation impact business processes and human interaction in the workplace. So, it became evident that adequate consideration of human factors is crucial for the success of digital transformation initiatives.

An important conclusion is that the success of Digital Transformation goes beyond merely adopting innovative technologies. It is essential to understand how these technologies affect the people involved in business processes and how to ensure that the changes implemented improve employees' experience and performance. These studies reveal the need for research that employs a conceptual model that effectively integrates human-centred design principles into implementing digital technologies within organisational contexts.

Upon recognising the significance of integrating these themes and observing through content analysis that no single article addressed all four research areas, a critical need emerged to understand better how these relationships and integrations could be achieved most beneficially. To explore this complexity, Structural Equation Modelling (SEM) was chosen as the method for further analysis. SEM allows for examining multiple variables and their interrelationships simultaneously, providing a comprehensive understanding of how digital transformation, human factors, business process management, and emerging technologies can interact. This method is particularly suited for exploring complex, multidimensional constructs, making it an ideal choice for investigating the nuanced and potentially impactful connections between these areas.

3.2. Partial Least Squares Structural Equation Modelling

PLS-SEM does not require a large sample size or specific assumptions about data distribution, including missing data. Researchers with small sample sizes and limited theoretical support can utilise PLS-SEM to examine causal relationships (Hair et al., 2021). So, this method is recommended for researchers in the initial stages or those with limited data who apply PLS-SEM to establish evidence for causal relationships and variable selection. This approach allows for ongoing data collection and hypothesis refinement (Hair et al., 2021).

The process of PLS-SEM involves some steps, as Hair et al. (2021) outlined. First, "Model Specification" is conducted, where the structural model is defined by identifying and specifying the relationships between latent variables (constructs). Additionally, the measurement model is determined by specifying how each latent variable is measured by its indicators (observed variables). Next, in the "Data Collection" phase, data is gathered for model estimation, ensuring that the sample size is adequate for robust analysis.

Following data collection, "Model Estimation" includes running the PLS-SEM algorithm. The "Model Estimation" involves estimating the outer model, which calculates the relationships between latent variables and their indicators, and the inner model, which estimates the relationships between the latent variables. The weights of the indicators for each latent variable are also determined during this step.

Subsequently, the "Assessment of the Measurement Model (Outer Model Evaluation)" takes place, where the reliability of individual indicators is assessed through measures such as Cronbach's alpha and Composite Reliability. Convergent validity is checked by evaluating the Average Variance Extracted (AVE) to ensure that the indicators of a latent variable are correlated. Discriminant validity is also confirmed to ensure that each latent variable is distinct from the others, using criteria like the Fornell-Larcker criterion.

The next step is the "Assessment of the Structural Model (Inner Model Evaluation)", where path coefficients are examined to assess the strength and significance of the relationships between latent variables. R-squared (R^2) values are also evaluated to determine the variance in the endogenous latent variables the model explains. Finally, the "Model Interpretation" step involves interpreting the results to draw meaningful conclusions from the analysis.

So, based on the theoretical study in the previous section, this research developed the hypothesis to examine the relationship between the DT and the relation among HFE, BPM and technologies. The hypotheses (H) of the model were formulated for testing in this research are detailed below:

- H1. The effective implementation of technologies, coupled with employee engagement and interoperability, drives the efficiency of digital transformation, promoting a user-friendly integration of processes with employees.

- H2. Employee awareness of digital transformation goals and the usability of technologies are essential for the success of digital transformation, promoting better adaptation to new platforms while potentially reducing the cognitive load associated with activities.
- H3. Implementing management technologies can result in significant gains in operational efficiency and improve decision-making through real-time analysis.
- H4. The effective implementation of BPM practices can result in improvements in the company's operational efficiency and enable quick adaptation to change in market conditions.

Therefore, in the following section, this paper describes the quantitative method used in this study. It is the most relevant selection method due to the research domain, data types, respondents' category, group, and data analysis tools and techniques.

3.2.1. Development of PLS-SEM

To start a project, we must prepare the path model demonstrating the relationship between the constructs. In PLS-SEM, the term construct is used to describe a variable that is not directly measured by indicators and, for that reason, is referred to as a latent variable (Hair et al., 2021). The structural equation modelling framework is subdivided into the structural and measurement models. The structural model specifies the relationships between the latent variables (constructs). In contrast, the measurement model defines how the observed variables (indicators) measure the latent variables, describing their validity and reliability (Duarte et al., 2016).

We must prepare the structural model to initiate the modelling process, demonstrating the relationships between the constructs. In PLS-SEM, the term "construct" describes a variable that is not directly measured and is therefore referred to as a latent variable. In this research, the pillars of RSL defined the constructs: Digital Transformation/Industry 4.0, Business Process Management, Emerging Technologies, and Ergonomics/Human Factors. These constructs were related, as presented in Figure 7. This relation was created based on the SLR results.

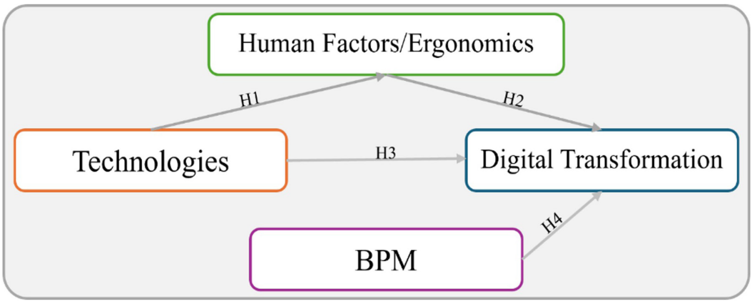

Figure 7. PLS-SEM structural model.

Thus, this model evaluates the proposed pathway (H1+H2) that effectively integrates human-centred design principles into implementing digital technologies within organisational contexts. This model means understanding how people interact with digital technologies in organisations and how this interaction can be made more effective and cognitively friendly. The model considers aspects such as people's cognitive thinking and how the organisation can be affected by introducing new technologies in pursuit of digital transformation.

This approach represents a more comprehensive view compared to other existing approaches analysed in the literature, such as the role of emerging technologies in digital transformation (H3) and BPM as an effective management strategy to achieve company objectives (H4). In other words, this model seeks to look beyond the simple implementation of technologies and management strategies.

Next, a set of indicators is necessary to measure the constructs. Indicators that cause the latent variable are called formative indicators. Conversely, indicators that are caused by the latent variable are called reflective indicators. To measure the latent variables, the indicators presented in Table 4 were created, and in this study, all indicators are reflective, meaning their respective areas of study cause them. These indicators were developed based on the content analysis of the articles resulting from the SLR, where the authors indicated in their research the benefits (gains), statements, and improvements generated regarding each latent variable.

Table 4. Indicators for each latent variable.

Code	Indicators	Ref.
DT1	By optimising operations, digital tools contribute to more efficient execution of daily tasks.	Richard et al. (2020); Golan et al. (2020); Papetti et al. (2020); Moencks et al. (2022)
DT2	Digital transformation drives value generation, helping the company align with market needs.	Liu et al. (2021); Hoch & Brad (2020); Martinez (2019)
DT3	Digital transformation streamlines internal processes, improving company productivity.	Parida et al. (2019); Martinez (2019); Richard et al. (2020)
DT4	Process automation enables replacing manual tasks with automated systems, providing efficiency, error reduction, and agility in task execution.	Richard et al. (2020); Butt (2020); Bellantuono et al. (2021); Hermann et al. (2019); Hoch & Brad (2020); Liu et al. (2021); Martinez (2019); Parida et al. (2019); Perez et al. (2022); Neumann et al. (2021); Kadir & Broberg (2021); Moencks et al. (2022)
DT5	Data collection and analysis facilitate informed decision-making, driving more effective strategies.	Liu et al. (2021); Perez et al. (2022)
HFE1	Investing in human factors promotes an engaging work environment, resulting in more productive and motivated employees.	Bellantuono et al. (2021); Butt (2020); Golan et al. (2020); Hermann et al. (2019); Kadir & Broberg (2021); Martinez (2019); Moencks et al. (2022); Neumann et al. (2021); Papetti et al. (2020); Parida et al. (2019); Richard et al. (2020)
HFE2	Human factors contribute to developing a solid organisational culture, with shared values and alignment of objectives.	Butt (2020); Papetti et al. (2020); Kadir & Broberg (2021); Parida et al. (2019)
HFE3	The participatory and human-centred approach aims to integrate the perspectives and experiences of individuals directly involved, promoting active collaboration and ensuring that solutions and decisions reflect user needs.	Bellantuono et al. (2021); Butt (2020); Kadir & Broberg (2021); Martinez (2019); Moencks et al. (2022); Neumann et al. (2021); Richard et al. (2020)
HFE4	Human-technology interaction seeks to create a harmonious relationship, facilitating the intuitive and beneficial use of technologies to improve workers' lives and experiences.	Butt (2020); Golan et al. (2020); Hermann et al. (2019); Kadir & Broberg (2021); Moencks et al. (2022); Papetti et al. (2020)
HFE5	Usability and user experience are significant factors regarding employees' use of technologies.	Butt (2020); Golan et al. (2020); Kadir & Broberg (2021); Moencks et al. (2022); Neumann et al. (2021); Papetti et al. (2020); Parida et al. (2019)
TEC1	Using indicators for business process management contributes to monitoring a company objective's performance level or success.	Butt (2020); Papetti et al. (2020); Kadir & Broberg (2021)
TEC2	Strategic planning can result in significant improvements in company operational efficiency.	Richard et al. (2020); Butt (2020); Perez et al. (2022); Golan et al. (2020); Hermann et al. (2019); Hoch & Brad (2020)
TEC3	Effective collaboration within a business ecosystem contributes to value aggregation and alignment of company demands.	Richard et al. (2020); Butt (2020); Parida et al. (2019)
TEC4	The process management approach constantly aims to promote a culture of continuous improvement to adapt to changes and challenges in the business environment.	Richard et al. (2020); Butt (2020); Martinez (2019); Parida et al. (2019)
TEC5	Effective management includes detailed mapping and documentation of each process, providing transparency and a clear understanding of the steps involved.	Bellantuono et al. (2021); Butt (2020); Heberle et al. (2017); Hermann et al. (2019); Kadir & Broberg (2021); Martinez (2019); Moencks et al. (2022); Richard et al. (2020)
BPM1	Process automation through technologies can reduce errors and increase consistency in operations.	Richard et al. (2020); Butt (2020); Bellantuono et al. (2021); Heberle et al. (2017); Hermann et al. (2019); Hoch & Brad (2020); Liu et al. (2021); Martinez (2019); Parida et al. (2019); Perez et al. (2022); Neumann et al. (2021); Kadir & Broberg (2021); Moencks et al. (2022); Papetti et al. (2020); Golan et al. (2020)
BPM2	Interoperability allows various systems to communicate with each other and share information in real-time.	Bellantuono et al. (2021); Butt (2020); Golan et al. (2020); Hermann et al. (2019); Kadir & Broberg (2021); Liu et al. (2021); Martinez (2019); Moencks et al. (2022); Papetti et al. (2020); Parida et al. (2019); Perez et al. (2022); Richard et al. (2020)
BPM3	Investing in cybersecurity and protecting the company from cyber threats is essential to keep sensitive data safe.	Butt (2020); Bellantuono et al. (2021); Heberle et al. (2017); Neumann et al. (2021); Parida et al. (2019)
BPM4	Technologies like Big Data directly contribute to operational efficiency, enabling more effective data management.	Butt (2020); Heberle et al. (2017); Hoch & Brad (2020); Kadir & Broberg (2021); Liu et al. (2021); Neumann et al. (2021); Parida et al. (2019); Perez et al. (2022)
BPM5	Using technologies provides access to real-time data and advanced analytics, facilitating informed and evidence-based decision-making.	Liu et al. (2021); Perez et al. (2022)

With the indicators defined, the measurement model can be established and used to assess the relationships between indicators and their corresponding constructs (Figure 8).

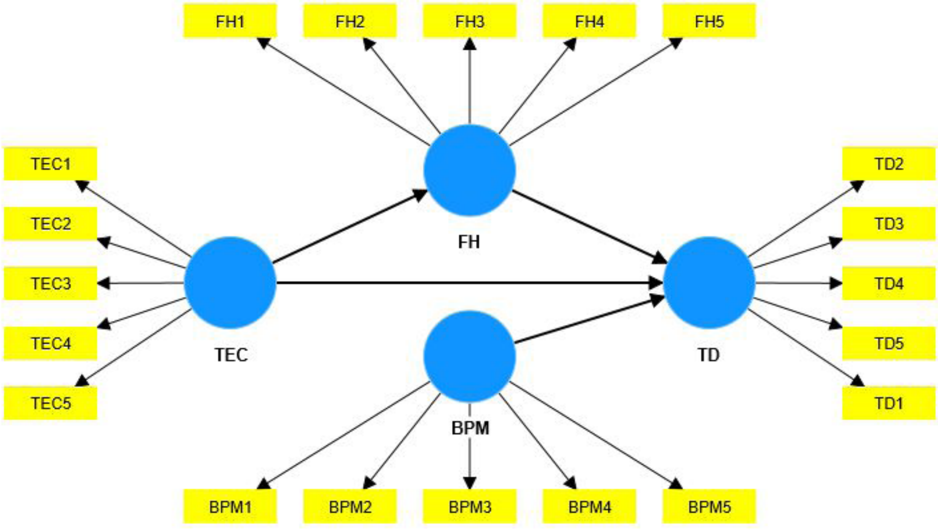

Figure 8. PLS-SEM measurement model.

3.2.2. Data collection

After the structural and measurement models were specified, a survey was conducted, utilising a structured questionnaire as the data collection instrument, through which information was requested from the group of respondents regarding the studied problem. Conclusions about the collected data were drawn through quantitative analysis. The sample was chosen by convenience, meaning it is non-probabilistic.

The questionnaire was emailed to a network of contacts in the industry, especially those connected to the industrial engineering field. These contacts, in turn, shared the questionnaire with colleagues in their respective sectors. Recipients included multinational companies, research groups, students, and professors from the Industrial and Systems Engineering Graduate Program at PUCPR. Additionally, the questionnaire was made available to members of the Brazilian Ergonomics Association (ABERGO), aiming to ensure the participation of experts from all relevant areas for the analysis.

For the evaluation of statements (indicators), a Likert scale with five response options was employed. According to Hair et al. (2011), Likert is a scale that attempts to measure attitudes or opinions, where five points are used to assess the strength of agreement or disagreement of a person with a set of statements. In this research, the agreement scale was defined as follows: (1) strongly disagree; (2) disagree; (3) neither agree nor disagree; (4) agree; and (5) strongly agree. As a result, 134 complete responses were obtained. Respondents who left questions unanswered were excluded from the sample, thus ensuring the integrity of the analysed data.

3.2.3. Measurement model evaluation

With the collected data, the next step is to execute the PLS-SEM algorithm and evaluate the reliability and validity of the construct measures in the measurement model based on the results.

According to Hair et al. (2022), the first evaluation should focus on internal consistency reliability. The internal reliability of the constructs was verified through Cronbach's Alpha and Composite Reliability indicators. Both indicators assess whether the sample has biases and whether the observed variables can generate reliable information (Hair et al., 2022). Composite reliability values from 0.60 to 0.70 are acceptable in exploratory research, while values between 0.70 and 0.90 can be considered satisfactory in more advanced stages of study (Hair et al., 2022). As can be observed in Table 5, the constructs in the model developed for this study exhibited adequate internal reliability.

The second criterion to be analysed is convergent validity, assessed through Average Variance Extracted (AVE). In this regard, a value of 0.50 or higher indicates that, on average, the construct explains more than the average variance of its indicators (Hair et al., 2022), with this being the minimum acceptable value for AVE. As shown in Table 5, the values found in the constructs were satisfactory.

The third and final criterion to be analysed is discriminant validity, assessed using the Fornell-Larcker criterion, which compares the square root of the AVE with the correlations between latent variables (Hair et al., 2022).

Table 6 presents the square root of the AVE for the model's constructs. It can be observed that the values of the square roots of the AVE for each construct are more significant than the correlations with other constructs. Thus, it is confirmed that the model has discriminant validity per the Fornell-Larcker criterion, a more conservative approach to ensure discriminant validity (Hair et al., 2022).

Table 5. Reliability and validity.

	Cronbach's alpha	Composite reliability (RHO_A)	Composite reliability (RHO_C)	Average variance extracted (AVE)
BPM	0.824	0.832	0.876	0.588
FH	0.796	0.810	0.859	0.550
TD	0.775	0.772	0.847	0.528
TEC	0.808	0.828	0.865	0.563

Table 6. Correlation between latent variables.

	BPM	FH	TD	TEC
BPM	0.767			
FH	0.504	0.741		
TD	0.475	0.395	0.726	
TEC	0.608	0.435	0.622	0.750

With these results, it is evident that the measurement model exhibits quality and confirmed validity, and now we proceed to the analysis of the structural model.

3.2.4. Structural model evaluation

The first analysis at this stage is the assessment of Pearson's determination coefficients (R^2): R^2 evaluates the portion of the variance in endogenous variables explained by the structural model. R^2 ranges from 0 to 1, with higher values indicative of greater explanatory power. As a general guideline, R^2 values of 0.750, 0.500, and 0.250 can be considered substantial, moderate, and weak, respectively (Hair et al., 2011).

In Figure 9, the values presented within the blue circles indicate how much of the variance of the latent variable is explained by the other latent variables contained in the structural model. In contrast, the values presented on the arrows, referred to as path coefficients (β), explain the strength of the effect of one construct on the others. Evaluating the degree of variance explanation of the target endogenous variable, in this case, TD, the R^2 was 0.412, which allows us to conclude that the three latent variables evaluated (TEC, FH, and BPM) weakly explain 41.2% of the variance of TD moderately.

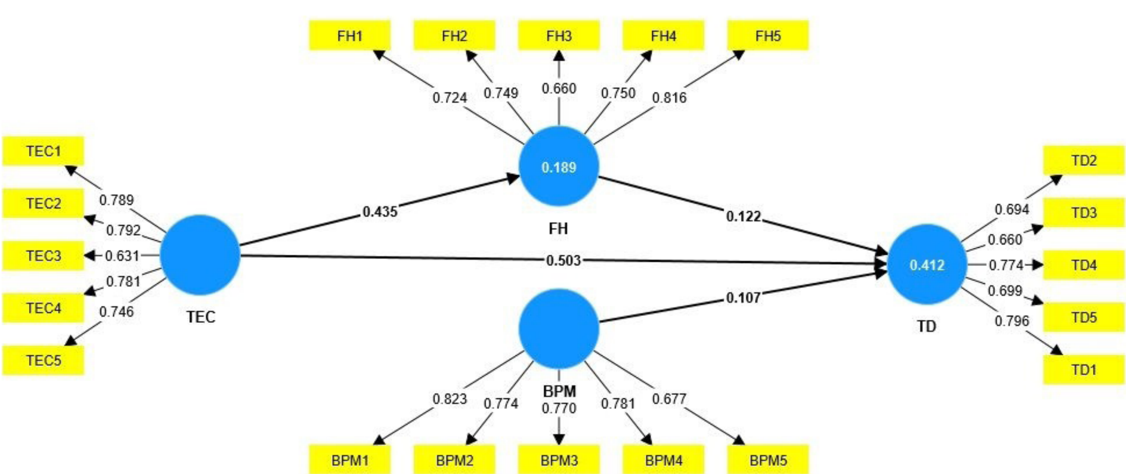

Figure 9. PLS-SEM results.

According to Hair et al. (2022), path coefficients are standardised values ranging between -1 and 1, where estimates close to 1 represent a strong positive relationship (and vice versa for negative values), and the closer to zero, the weaker the relationship. When analysing the path coefficients, it is observed that the relationship TEC>TD, referring to H3, has a moderate relationship ($\beta = 0.503$). However, when analysing the path TEC>FH>TD, referring to hypotheses H1+H2, the relationship is more robust ($\beta = 0.557$) than the TEC>TD path alone since the sum of the path is more significant. This analysis indicates that the path with the better result is more recommended, as the relationships between the variables are more satisfactory when seeking the outcome of digital transformation.

Furthermore, when analysing each construct's observed variables (indicators), all indicator loadings should be statistically significant, with standardised loadings expected to exceed 0.708. Indicators with loadings between 0.400 and 0.700 should be scrutinised and eliminated only if they impact the reliability and quality of the model (Hair et al., 2011).

Most indicators exhibited loadings exceeding 0.708; only indicators TEC3, FH3, BPM5, TD2, TD3, and TD5 showed values slightly below but close to the recommended value. Additionally, the model demonstrated satisfactory Cronbach's Alpha, Composite Reliability, and AVE; the indicators were retained for these reasons.

Finally, examining the highest loadings of the indicators for each construct, we have indicators TD1 (By optimising operations, digital tools contribute to more efficient execution of daily tasks), FH5 (Usability and user experience are significant factors regarding the use of technologies by employees), TEC2 (Interoperability allows various systems to communicate with each other and share real-time information), and BPM1 (The use of indicators for business process management contributes to monitoring the level of performance or success of a company's objective).

4. Discussion of results

The discussion of results emphasises critical findings regarding integrating digital transformation (DT) in organisational processes, particularly its impact on human factors and business process management. It highlights several meaningful insights and offers a structured approach to implementing digital initiatives effectively.

Firstly, digital tools play a crucial role in optimising the execution of daily tasks, leading to enhanced organisational efficiency. However, successful digital transformation extends beyond mere automation; digital tools must align with usability and user experience principles. Ensuring a harmonious interaction between employees and technology minimises cognitive strain and potential resistance to change, which supports smoother adaptation to new platforms and boosts productivity.

The study underscores the importance of incorporating strategic indicators, such as Key Performance Indicators (KPIs), in digital transformation efforts. KPIs provide a framework for monitoring progress and evaluating the success of digital initiatives, allowing organisations to make data-driven decisions and promptly adjust strategies. This real-time tracking of business objectives facilitates evidence-based management, where precise insights rather than assumptions guide decisions.

Interoperability, the ability for various systems to communicate and share information seamlessly, emerges as a critical efficiency driver. By enabling real-time data exchange across different departments and systems, interoperability fosters collaboration and promotes a unified approach to operations. The interconnectedness ensures that data flows freely, breaking down silos and equipping all stakeholders with the information needed to make informed decisions.

Building on these insights, the study proposes a conceptual model based on Partial Least Squares Structural Equation Modelling (PLS-SEM) findings. The model provides a theoretical framework to understand the relationships among digital transformation, human factors, business process management, and emerging technologies. It suggests that the optimal path for digital transformation integrates the human dimension as a central aspect of technological progress, balancing the pursuit of efficiency with employee well-being.

A significant finding is the crucial role of human factors in the success of digital transformation initiatives. The research indicates that implementing technologies without considering their impact on employees' cognitive and emotional well-being can lead to increased stress, resistance to change, and reduced productivity. Human-centred design principles should be employed to address these challenges, involving employees in the design and implementation processes to ensure solutions meet their needs. This approach reduces cognitive overload, enhances user satisfaction, and fosters a positive technological adoption experience.

The discussion also stresses that sustainable digital transformation requires cultural and organisational changes beyond technical improvements. Companies must invest in training programs to help employees develop the skills needed for a digital environment. Leadership is vital in nurturing a culture that embraces change and innovation, essential for ongoing improvement and adaptability in response to technological advancements. Integrating human factors into the digital strategy allows organisations to create a supportive work environment that drives efficiency while contributing to employee well-being.

Therefore, the discussion advocates for a balanced approach to digital transformation that integrates technological advancement with employee engagement, usability, and well-being considerations. The findings support a human-centric model that not only optimises organisational processes but also aids the workforce in adapting to the evolving digital landscape, ensuring long-term success and sustainability.

5. Conclusion

In conclusion, this study demonstrates that human factors play a crucial role in the success of digital transformation initiatives. The findings highlight that technologies must be implemented to align with employees' cognitive and emotional well-being to ensure effective adoption and optimal productivity. A key insight is the need for human-centred design principles, which help reduce cognitive overload and enhance employee satisfaction. Moreover, the results reinforce the importance of cultural and organisational changes, such as leadership support and continuous training, to sustain digital transformation.

This study also addresses the social aspects of implementing digital technologies in the workplace. It considers the impact of these technologies on workers' quality of life and changes in the job market due to automation. Additionally, it highlights the importance of understanding and incorporating changes in social behaviour caused by digital advancements. The study examines digital transformation's technical and organisational implications and social aspects.

For future research, the following steps involve elaborating on the conceptual model derived from the PLS-SEM results. This model will comprise a systematic arrangement of variables and their interrelationships, providing a comprehensive overview of the research domain. Each model component will be meticulously defined, drawing upon theoretical foundations and empirical evidence uncovered in the study. Furthermore, the model will be subjected to rigorous validation procedures to ensure its robustness and applicability. Once finalised, the conceptual model will guide future research endeavours and practical implementations for companies.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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