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AI Related Technostress: A Systematic review of Workload, Incompetence in Relation to Employee Turnover Intention

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ABSTRACT: The increasing integration of AI in the workplace is transforming job roles, performance expectations, and employee experiences. While AI has the potential to enhance efficiency and decision-making, it may also introduce new challenges, including workload and technological complexity, which can lead to employee technostress and turnover intentions. This systematic review investigates the relationship between AI-related work demands, technostress, and turnover intention, and examines the role of organizational support in alleviating these effects. The literature was sourced from databases including Scopus, ScienceDirect, Google Scholar, and Web of Science, with the final search conducted on 15 September 2026. Studies were selected based on predefined inclusion and exclusion criteria, and their methodological quality was evaluated according

to the information provided. Findings were synthesized narratively by identifying common themes and relationships among key variables, without meta-analysis. Twenty-five studies were included, focusing on AI usage, workload, lack of technological competence, technostress, employee well-being, organizational support, and turnover intention. The results indicate that AI-related work demands, particularly workload, technological complexity, can increase technostress and turnover intention. Organizational support may play a crucial role in mitigating these adverse effects. However, the existing evidence is constrained by variations in study contexts, research designs, and measurement methodologies, with limited longitudinal data. The findings underscore the necessity for employee training, competence development, and organizational support alongside AI implementation. This review suggests the concept of AI-Specific Organizational Support (AI-SOS) as a potential mediator between AI-related technostress and turnover intention. No external funding was received, and review was not prospectively registered.

INTRODUCTION

Digital technologies have significantly altered work procedures and organizational structures across various industries. Among these technologies, artificial intelligence (AI) has emerged as a crucial factor in enhancing organizational efficiency, capabilities, and data-driven decision-making. AI-enabled systems are increasingly being integrated into workplace activities, thereby transforming how employees execute tasks, engage with technology, and respond to changing work requirements. These transformations may introduce new AI-related work demands, such as technology-driven workloads, the necessity to learn new systems, adaptation to technological changes, and the development of competencies essential for effective collaboration with AI-enabled tools. The Job Demands–Resources (JD-R) model posits that job demands can become a source of strain when they necessitate sustained effort and surpass the resources available to employees (Bakker and Demerouti, 2007). In technology-intensive work environments, factors such as technology overload, complexity, and rapid technological changes have been recognized as significant sources of technostress (Ayyagari et al., 2011; Tarafdar et al., 2007). The growing prevalence of AI may introduce an additional layer of technological demands, particularly for employees who must continuously learn, adapt, and sustain their effectiveness while engaging with evolving AI-based systems.

Technostress is the stress that arises when people find it challenging to manage or adjust to demands associated with technology. In the context of organizations, this type of stress can stem from overwhelming workloads, the complexity of technology, uncertainty, and the ongoing necessity to learn and adapt to new technological advancements (Tarafdar et al., 2007; Tarafdar et al., 2015). This problem is especially pertinent in workplaces that utilize AI, as AI systems can modify job responsibilities, alter performance expectations, and change the skills needed to carry out tasks. Employees may feel increased psychological pressure and face adaptation challenges in a shifting work environment when they believe that technological demands surpass their available skills or resources (Ayyagari et al., 2011).

Turnover intention, a significant outcome related to employee stress and technological pressures, is defined as an employee's deliberate consideration or plan to leave their current organization. Continuous stress from work and challenges in meeting workplace demands can affect how employees perceive their jobs and their decision to stay with the company. Previous studies have shown connections between technostress and employee outcomes, and more recent research has focused on these connections within AI-driven work settings. Nonetheless, the current body of literature addresses various technological pressures, employee groups, workplace environments, and outcomes. Therefore, it is crucial to explore the relationship between AI-related work demands, technostress, and employee turnover intention in a comprehensive way.

Beyond the demands placed on individual employees, the organizational environment can shape how they react to technological changes. Organizational support is generally understood as the perception among employees that their organization values their contributions and is concerned about their well-being (Eisenberger et al., 1986; Rhoades and Eisenberger, 2002). In workplaces that incorporate AI, this support might include AI related training, technical guidance, access to necessary resources, opportunities for skill enhancement, and managerial help. Such support becomes crucial when employees must acquire new technological skills and adapt to evolving AI-driven job roles. Consequently, AI-Specific Organizational Support (AI-SOS) can be seen as a tailored organizational resource that aids employees in handling AI-related work pressures and technostress.

While there has been an increase in studies focusing on AI-driven workplace transformations and stress related to technology, the research remains scattered across various constructs, employee demographics, and study environments. Although previous reviews have addressed broader issues of technostress, AI's role in organizational settings, and stress caused by AI, the specific connection between AI-related job demands, technostress, and the intention of employees to leave their jobs has not been comprehensively analyzed. Moreover, even though organizational support is often viewed as a general workplace resource, the specific impact of AI-Specific Organizational Support on the link between AI-related technostress and turnover intention needs more detailed exploration. Therefore, a systematic review is essential to integrate these related areas of research, highlight areas of consensus and debate, and clarify the interactions among AI-related job demands, technostress, turnover intention, and organizational support.

Accordingly, this systematic review asks: How are AI-related work demands, technostress, and employee turnover intention related, and what potential role may AI-Specific Organizational Support (AI-SOS) play in these relationships.

MATERIALS AND METHODS

ELIGIBILTY CRITERIA

Studies were deemed eligible if they directly contributed to one or more of the key constructs addressed in the review, such as the use of Artificial Intelligence (AI) in the workplace, AI-related work overload, technological competence, technostress, employee turnover intention, and AI-specific organizational support or organizational support. It was not necessary for a study to examine all these constructs simultaneously, as long as it provided pertinent evidence or theoretical insights relevant to the review's objectives. The review specifically targeted employees, working professionals, and workplace environments. Studies focused solely on students, learners, or educational populations lacking a relevant employee or workplace context were excluded. Additionally, studies were excluded if their primary emphasis was unrelated to the review's objectives or if they did not furnish relevant information concerning any of the key constructs considered in the review. The review encompassed empirical, review, and conceptual or theoretical publications that directly contributed to the evidence base or theoretical foundation of the review. Only journal articles and research papers published in English were considered eligible. The publication period spanned from 1984 to 2026, enabling the review to incorporate foundational literature on technostress, job demands and resources, and organizational support, along with more recent literature addressing AI-related workplace demands and employee outcomes. Studies were included if they measured, examined, discussed, or provided a theoretical foundation for at least one relevant construct or relationship within the review framework. Publications were included if they addressed at least one of the key areas pertinent to the review, even if they did not analyze all variables collectively. For synthesis, the included publications were categorized according to their primary contribution to the review: (i) use of AI at work; (ii) AI-related work demands and workload; (iii) technological competence, technological complexity, and technostress; (iv) employee outcomes and turnover intention; and (v) organizational support and AI-Specific Organizational Support (AI-SOS). These categories facilitated the organization of findings and the development of an integrated narrative synthesis of the relationships among the key constructs, which informed the proposed conceptual framework.

INFORMATION SOURCES

Relevant literature was identified through searches conducted on Scopus, Web of Science, ScienceDirect, and Google Scholar. Scopus database was accessed via the Elsevier Scopus interface, while the Web of Science was explored through the Web of Science Core Collection (Clarivate), both used as bibliographic databases. ScienceDirect was utilized as a platform for scholarly literature, and Google Scholar as a scholarly search engine, accessible through https://scholar.google.com/. The review considered publications released between 1984 and 2026, in line with predefined eligibility criteria. These sources were chosen to identify relevant research on artificial intelligence (AI) in the workplace, AI-related work demands and workload, technological incompetence, technostress, employee turnover intention, and organizational support, including AI-Specific Organizational Support (AI-SOS). The last search on Google Scholar occurred on 30 July 2026, while searches on Web of Science, Scopus, and ScienceDirect were conducted on 9 September 2026 and 15 September 2026, respectively. In addition to these electronic searches, reference lists of studies included in this review were scrutinized to uncover potentially eligible studies that may not have been retrieved through the database searches. No study registries, clinical trial registries, or other research repositories were examined, as the review concentrated on workplace and organizational research rather than clinical interventions. Citation searching of cited or citing publications was not performed, and no specific journals or conference proceedings were examined

separately. Furthermore, no authors, researchers, organizations, or manufacturers were contacted to identify additional studies or acquire unpublished information.

SEARCH STRATEGY

A structured, keyword-based search strategy was formulated to identify literature relevant to the objectives of the review. This strategy was organized around the primary conceptual areas of the review, specifically the use of Artificial Intelligence (AI) in the workplace, AI-related workload and work demands, challenges associated with technological competence, technostress, employee turnover intention, and AI-Specific Organizational Support (AI-SOS). Individual keywords, as well as combinations of keywords, were searched across databases such as Scopus, Web of Science, ScienceDirect, and Google Scholar. The main search terms included "use of AI at work," "AI-related workload," "AI-related work overload," "technological competence," "lack of technological competence," "technostress," "employee turnover intention," "organizational support," and "AI-Specific Organizational Support." Quotation marks were utilized around specific multi-word phrases when appropriate, while the Boolean operator AND was employed in selected searches to combine major conceptual areas. Searches incorporating relevant author names were also performed to identify additional publications related to AI, technostress, organizational support, and employee outcomes. Individual and combined searches were conducted iteratively to capture literature employing various terminologies across the selected information sources. Representative reconstructed search terms and combinations utilized across these sources are presented in Table 1. Due to the absence of complete search logs for all search sessions, the reported search strategy outlines the principal keywords, combinations, filters, and search methodologies employed during the review, without serving as a verbatim record of every individual search query. In Scopus, individual and combined keyword searches were executed using the TITLE-ABS-KEY field, where applicable, to identify records containing relevant terms in the title, abstract, or author keywords. The search results were refined using available source and document-type options, considering Journal and Book Series publications while excluding Conference Proceedings. Searches were limited to English-language publications, and only those publications that fell within the review's predefined eligibility period were considered.

Web of Science: A similar methodology was employed using both individual and strategically combined keyword searches. Quotation marks were utilized for precise phrases, and the AND operator was applied to combine selected concepts. Relevant author names were also searched independently. The search was confined to publications in the English language, and the retrieved records were evaluated based on the established eligibility criteria. No further restrictions concerning document type were imposed during the search.

ScienceDirect: The searches conducted on ScienceDirect adhered to the conceptual approach used in Scopus. Individual keywords, along with specific combinations of the primary review constructs, were searched using quotation marks and the AND operator when applicable. Additionally, relevant author names were searched independently. The search concentrated on English-language literature, considering publications from journals and book series while excluding conference proceedings. Subsequently, the records were evaluated against the established eligibility criteria.

Google Scholar: Google Scholar served as an additional scholarly search engine to enhance the identification of pertinent literature. Individual conceptual terms and specific combinations were searched using AND, with quotation marks applied to particular phrases as necessary. Searches based on authors were also conducted. Searches were performed both with and without year restrictions. Year-based searches were selectively employed to identify recent publications, while searches without year restrictions aimed to uncover foundational literature. The "include citations" option was utilized in certain searches where applicable; however, this was not regarded as formal citation searching of citing publications. Google Scholar searches were confined to literature in the English language.

Search Development and Review - The search strategy was developed iteratively based on the major constructs and terminology identified during the initial examination of relevant literature. Guidance was obtained from experienced faculty members regarding appropriate keywords, relevant scholarly databases, and suitable sources for the review. The retrieved literature and the databases from which the publications were obtained were also discussed with a faculty member to assess the relevance and credibility of the sources and to identify additional databases that could strengthen the literature search.

AI tools were only used for the initial phase of brainstorming potential keywords and did not shape the final search strategy. No natural language processing, text-frequency analysis, or automated keyword-generation software were used to systematically create, refine, or rank search terms. Instead, the final keywords were mainly identified by reviewing relevant literature and

guidance with faculty members and experienced researchers. No existing search filter or strategy was directly applied in this review. Additionally, no automatic translation tool was used to convert search strings between database platforms; instead, search terms were manually adjusted to align with the search interfaces and functionalities available in each information source.

The search strategy was not formally validated against a predefined set of known relevant studies and did not undergo peer review utilizing a structured tool such as the PRESS (Peer Review of Electronic Search Strategies) checklist. Nevertheless, the search process and the literature retrieved were informally reviewed by a faculty member, who assessed the databases used, the collected papers, and the relevance and authenticity of the sources. Given that the current review concentrates on workplace and organizational phenomena rather than clinical interventions, the search strategy did not adhere to the PICO framework. Instead, it followed a conceptual search structure based on the primary constructs of the review: (i) the use of AI in the workplace, (ii) AI-related work demands and workload alongside challenges related to technological competence, (iii) technostress, (iv) employee turnover intention, and (v) organizational support, specifically AI-Specific Organizational Support (AI-SOS). Individual and combined searches across these conceptual domains were conducted to identify literature pertinent to the review objectives.

Information Source	**Representative Search Term and Combinations**	**Search Approach**	**Filters**
Scopus	AI use at work; AI workload; technological competence; technostress; turnover intention; organizational support	Individual and combined keyword searches using **AND**	English; relevant journal and book-series publications
Web of Science	AI use at work; AI workload; technological competence; technostress; turnover intention; organizational support	Individual and combined keyword searches using **AND**	English
Science Direct	AI use at work; AI workload; technological competence; technostress; turnover intention; organizational support	Keyword searches using individual and combined terms	English; relevant journal and book-series publications
Google Scholar	AI use at work; AI workload; technological competence; technostress; turnover intention; organizational support	Keyword and phrase searches, including combined terms	English-language publications

Table 1: Represents search terms and combinations

STUDY SELECTION PROCESS

The publications identified through Scopus, Web of Science, ScienceDirect, and Google Scholar were systematically collected and organized according to their respective information sources. Initially, a total of 47 publications were compiled for evaluation. The selection process adhered to a sequential screening of titles, abstracts, and full texts based on predefined eligibility criteria. The faculty supervisors collaboratively assessed each publication for its relevance to the review objectives, employee/workplace demographics, and key conceptual areas, including the use of artificial intelligence (AI) in the workplace, AI-related work demands or workload, technological competence related challenges, technostress, employee turnover intention, and organizational support. During the screening process, one duplicate publication was eliminated, and 21 publications were excluded due to insufficient alignment with the review objectives, target population, or conceptual scope. Publications that were only marginally relevant to areas such as recruitment, without adequate connections to the core constructs of the review, were also excluded. Only publications written in English were deemed eligible. Following the screening and eligibility assessment, 25 publications were retained for the final synthesis.

The faculty supervisor offered methodological guidance throughout the selection process, which included assistance in identifying pertinent databases and keywords, applying search filters, checking for duplicates, and evaluating the relevance and eligibility of publications. AI tools were utilized solely as supplementary aids to clarify the content and relevance of potentially includable or excludable publications; they were not employed for independent screening or final decision-making. The final decisions regarding inclusion and exclusion were made collaboratively by the faculty supervisor. The screening process was conducted manually, without the use of specialized systematic-review software, automated screening platforms, or machine-learning classifiers. No authors of the studies were contacted for additional information, and a formal disagreement-resolution procedure was unnecessary, as no significant disagreements arose. In addition to the results obtained from databases and search engines, the reference lists of included publications were manually reviewed to identify additional potentially relevant publications that were not retrieved during the initial searches. Publications identified through this process were evaluated using the same eligibility criteria. Formal citation analysis of citing publications was not performed. Given that the review was confined to English-language publications, no translation was necessary.

DATA COLLECTION PROCESS

The researcher extracted and documented information from the 25 selected publications after a comprehensive review of their full texts. For each publication, relevant details aligned with the review objectives were recorded, including the author(s) and year, study objective or topic, sample and population as reported, methodology, variables or constructs, theoretical framework, main findings, relationships between variables, limitations, and research gaps. The information was systematically organized in a Microsoft Word document, featuring distinct sections and consistent subheadings for each publication. This approach facilitated a clear record of the evidence and enabled comparisons of findings across the included literature.

The information extracted was evaluated by the faculty supervisor for accuracy, relevance, and interpretation, no formal independent duplicate extraction was conducted. AI tools were utilized only as a limited supplementary resource, primarily to elucidate study objectives, variables, research gaps, and methodological details. The researcher retained responsibility for reading, extracting, interpreting, and recording the information, and AI tools were not employed as automated extraction tools or independent reviewers. No specialized data-extraction software or automated tools were utilized. Furthermore, no authors of the studies were contacted for additional information, and no translation was necessary, as only publications in English were included. Numerical data were not extracted separately from figures or tables for statistical analysis; rather, the reported findings and relationships were qualitatively examined for narrative synthesis. Additionally, no multiple reports of the same study were identified.

DATA ITEMS

The data items were crafted in alignment with the review's goals and conceptual boundaries. The primary focus was on the intention of employees to leave their jobs, which indicates their plans or thoughts about departing from the organization. Additionally, the review captured other significant outcomes mentioned in the publications, such as job satisfaction, organizational commitment, emotional exhaustion, burnout, employee well-being, work-life balance, work performance or productivity, role stress, engagement, and career growth. The review emphasized the core elements of the proposed framework, which include the use of AI in the workplace, AI-related workload or work demands, technological competence or its absence, technostress, employee turnover intention, and organizational support, including AI-Specific Organizational Support (AI-SOS). Publications were considered pertinent if they provided evidence or theoretical insights into any of these elements or their interconnections. For each of the 25 publications analyzed, details such as the authors and publication year, study objectives, sample and population (when available), methodology, variables or constructs, theoretical framework, primary findings, relationships among variables, limitations, and research gaps were systematically documented. Definitions and interpretations of key constructs were compared across the studies, with differences being acknowledged rather than assumed to be the same. Findings were assessed based on their relevance to the review's objectives, without emphasizing statistical significance or the direction of relationships. Missing or unclear information was neither estimated nor assumed, and no authors were contacted for further details. The publication year was noted, but outcome measurement time points were not considered for inclusion or exclusion. No numerical conversions, calculations, or statistical transformations were conducted. A predefined published extraction checklist was not utilized; instead, the researcher created a structured format in Microsoft Word with uniform sub-

headings for each publication. The study encompassed the objective, variables or constructs, theoretical framework, methodology, sample or population, findings, relationships, limitations, and research gaps. This approach enabled consistent documentation and facilitated comparison across the literature reviewed.

STUDY RISK OF BIAS ASSESSMENT

The methodological quality and relevance of the 25 publications included in the review were evaluated during the review process. Given that the literature encompassed various research designs and purposes, a single formal risk-of-bias or study-quality assessment tool was not uniformly applied across all publications. Instruments such as JBI, CASP, MMAT, or other standardized risk-of-bias tools were not utilized. Instead, the assessment relied primarily on a qualitative information presented in each publication, with particular emphasis on the clarity and relevance of the study methodology, the study population or context where applicable, the variables or constructs investigated, the theoretical or conceptual framework, and the degree to which the reported findings aligned with the objectives of the current review. This assessment aimed to facilitate the interpretation and synthesis of the literature, rather than to assign a numerical quality score to individual publications.

The initial evaluation of the methodological and substantive information was performed by the researcher, followed by a review of the extracted information and assessment by the faculty supervisor. The faculty supervisor offered guidance in evaluating the quality and relevance of the publications, as well as in determining whether the reported evidence was sufficiently aligned with the objectives and conceptual scope of the review. The researcher and faculty supervisor does not categorize studies into predefined classifications such as low, moderate, or high risk of bias, and no overall numerical risk-of-bias score was computed. Given the diversity in methodological and conceptual purposes among the included publications, their quality and relevance were assessed in relation to the type and contribution of each publication. Empirical studies were evaluated based on their reported methodology, population, variables, and findings, while review, conceptual, and foundational publications were primarily assessed for their relevance and contribution to the theoretical and conceptual understanding of the constructs examined in the review. No publication was excluded solely based on a formal risk-of-bias score, as a standardized risk-of-bias scoring system was not implemented. Additionally, no supplementary information was solicited from study authors or investigators for the purpose of evaluating methodological quality. AI-based tools were not utilized to assess study quality or risk of bias; this aspect of the review was supported by the researcher and faculty supervisor.

EFFECT MEASURES

In the present review, a common statistical effect measure was not utilized due to the absence of quantitative combinations of the included publications and the lack of a meta-analysis. Instead, the review employed a narrative synthesis approach, whereby findings from the included publications were thematically compared based on their relevance to the primary constructs and relationships explored in the review.

The review did not preselect or extract a specific statistical effect measure, such as risk ratios, odds ratios, mean differences, correlation coefficients, regression coefficients, or effect sizes. Reported numerical results were not systematically extracted, combined, converted, or standardized across studies. Likewise, no thresholds were established to classify effects as small, moderate, or large. Instead, the synthesis emphasized the direction, nature, consistency, and conceptual relevance of the relationships and findings reported across the publications, including areas where findings diverged or exhibited contrasting pathways. This methodology was employed due to the variability in study designs, constructs, measures, populations, and research contexts among the included literature, rendering a common quantitative effect measure unsuitable for this review.

SYNTHESIS METHODS

The findings from the 25 included publications were synthesized through a narrative synthesis approach. This method was considered appropriate due to the variations among the publications in terms of research objectives, study populations, workplace contexts, theoretical perspectives, variables, and reported findings. Consequently, the findings were compared qualitatively rather than being statistically combined.

For each publication, the researcher conducted a thorough review of the full text and documented the relevant information in a structured Word document. Each publication was organized separately and assessed under common headings, which included the study objective or topic, variables and constructs, theoretical framework, methodology and sample characteristics (when

reported), main findings, relationships between variables, limitations, and research gaps. This approach provided a consistent framework for evaluating the contributions of each publication to the review.

Following the review of individual publications, their findings were compared across the literature to identify recurring themes and relationships among key constructs. Particular attention was directed towards the nature of relationships reported in the literature, specifically regarding whether a variable was associated with positive or negative employee outcomes. The comparison also took into account common findings, contrasting results, theoretical perspectives, and variations in study populations and workplace contexts. For instance, relationships involving AI-related work demands, technostress, employee turnover intentions, and organizational support were examined across the included literature.

The synthesis was structured around the primary conceptual areas of the review: the use of AI in the workplace; AI-related work demands and workload; challenges associated with technological competence; technostress; employee turnover intentions; and organizational support, including AI-Specific Organizational Support (AI-SOS). The findings identified within these areas were integrated to develop a comprehensive understanding of how the major constructs may be interconnected. This synthesis served as the foundation for the proposed conceptual framework presented in the review.

No meta-analysis or statistical synthesis was performed, as the studies did not yield sufficiently comparable outcomes, measures, and research designs for the statistical pooling of results. Consequently, effect sizes were neither calculated, converted, standardized, nor statistically combined, and no statistical software was utilized for synthesis. Therefore, formal statistical tests of heterogeneity, subgroup analysis, and meta-regression were not applicable to the present review.

Differences among studies were qualitatively assessed during the narrative synthesis, particularly concerning research context, population, theoretical perspective, constructs examined, and direction of findings. The final synthesis was based on the 25 publications retained following the study selection process; no additional studies were removed or reintroduced for the purpose of conducting a sensitivity analysis.

REPORTING BIAS ASSESSMENT

The review did not formally assess the risk of bias stemming from missing or selectively reported results. No established tools for reporting bias, graphical methods, or statistical tests were employed. Instead, the researcher examined the reported outcomes and findings relevant to the review objectives and documented the available information concerning key variables and relationships. Most of the included publications contained relevant findings.

Reporting bias was not evaluated as a distinct domain during the study selection or narrative synthesis, nor was any publication excluded specifically due to concerns about missing or selectively reported results. The faculty supervisor evaluated the overall quality and relevance of the publications; however, a separate assessment of reporting bias was not performed. Additionally, no authors or investigators were contacted regarding potentially missing results, and no automated or AI-based tools were utilized for this evaluation. Given that the review employed narrative synthesis without statistical pooling, the potential impact of missing results on the overall synthesis was not quantitatively assessed. The lack of a formal reporting-bias assessment is recognized as a methodological limitation and was taken into account when interpreting the synthesized findings.

CERTAINITY ASSESSMENT

The certainty of the available evidence was qualitatively assessed across the 25 publications included in the review. The researcher evaluated the quality and relevance of each publication, the consistency of findings, methodological characteristics, and alignment with the review objectives when interpreting the overall evidence. No formal certainty-of-evidence framework or standardized tool, such as GRADE, was utilized; consequently, the evidence was not categorized into high, moderate, low, or very low certainty levels. A qualitative approach was considered appropriate due to the variability in research design, population, workplace context, theoretical perspective, constructs, and outcomes among the included publications. Thus, consistent and contrasting findings were interpreted in relation to these methodological and contextual differences rather than through a singular quantitative criterion.

The assessment was primarily conducted by the researcher, with the faculty supervisor reviewing the quality and relevance of the publications and providing methodological guidance. No independent duplicate assessment or formal disagreement-resolution procedure was employed, and no authors were contacted for additional information. As the review utilized narrative

synthesis without statistical pooling or standardized effect measures, no predefined thresholds for imprecision, effect magnitude, or statistical heterogeneity were established. Existing certainty tools were not adapted, and artificial intelligence or automated tools were not employed to determine certainty. Findings were presented through narrative synthesis and paper-wise comparison rather than through formal certainty ratings or a Summary of Findings table. The study characteristics/outcome table was utilized solely for organizing the evidence and was not regarded as a certainty-assessment tool. The lack of a formal certainty assessment is acknowledged as a limitation of the review.

RESULTS AND DISCUSSION

STUDY SELECTION

The comprehensive process of publication identification, screening, eligibility assessment, exclusion, and final inclusion is illustrated in Figure 1. A total of 47 publications were identified through Scopus, Web of Science, ScienceDirect, and Google Scholar. Following the removal of one duplicate, 46 publications were screened based on their titles and abstracts. Of these, 21 were excluded due to insufficient relevance to the predefined eligibility criteria and the primary focus of the review. The remaining 25 publications underwent full-text assessment and were included in the final narrative synthesis. Selection decisions were made with guidance from faculty members.

STUDY CHARACTERISTICS

Table 2 presents the characteristics of the 25 included publications. These publications encompass foundational, empirical, review, and conceptual work pertaining to technology-related work demands, technostress, employee outcomes, AI utilization, and organizational support. The studies varied in terms of their populations, research designs, and focal constructs. These characteristics were taken into account when comparing the evidence and formulating the subsequent thematic synthesis.

No.	Citations	Title of the publication	Focus of the Study	Context	Method	Key finding relevant to the review
1.	(Ayyagari et al., 2011)	Technostress: Technological Antecedents and Implications	Examined technological antecedents and implications of technostress.	661 working professionals	Empirical	Work overload and role ambiguity were prominent technostress-related stressors.
2.	(Ragu-Nathan et al., 2008)	The Consequences of Technostress for End Users in Organizations: Conceptual Development and Empirical Validation	Examined the consequences of technostress and the role of technostress inhibitors.	608 ICT end users	Empirical, SEM	Technostress creators were associated with lower job satisfaction and organizational commitment, while inhibitors showed beneficial relationships.
3.	(Tarafdar et al., 2007)	The Impact of Technostress on Role Stress and Productivity	Examines technostress, role stress and productivity	ICT users in 223 organizations	Empirical, SEM	Technostress was positively related to role stress and negatively related to

						individual productivity.
4.	(Califf and Brooks, 2020)	An empirical study of techno-stressors, literacy facilitation, burnout, and turnover intention as experienced by K-12 teachers	Examines techno-stressors, burnout, literacy facilitation and turnover intention	416 U.S. K–12 teachers	Empirical	Techno-insecurity, invasion and overload increased burnout; burnout was positively related to turnover intention, while literacy facilitation had a mitigating role.
5.	(Karr-Wisniewski and Lu, 2010)	When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity	Examines technology overload and its dimensions	Knowledge workers	Empirical	Information, communication and system-feature overload were linked to productivity loss.
6.	(La Torre et al., 2024)	Effects of technostress on the productivity of workers in ICT company: an observational study	Examines technostress and worker productivity	ICT company workers	Observational study	Provides workplace evidence on the relationship between technostress and productivity.
7.	(Fischer and Riedl, 2017)	Technostress Research: A Nurturing Ground for Measurement Pluralism?	Reviews measurement approaches in technostress research	103 empirical technostress studies	Review	Shows substantial variation in how technostress has been conceptualized and measured.
8.	(Bakker and Demerouti, 2007)	The Job Demands–Resources model: State of the art	Develops the JD-R framework	JD-R Framework	Theoretical review	Provides the main theoretical basis for understanding job demands, resources and employee strain.

9.	(Demerouti et al., 2001)	The job demands-resources model of burnout	Develops and tests the JD-R model of burnout	374 employees across occupational groups	Empirical	Job demands were associated with exhaustion, while lack of resources was associated with disengagement.
10.	(Eisenberger et al., 1986)	Perceived Organizational Support	Introduces the perceived organizational support perspective	Employees	Theoretical/empirical foundation	Establishes organizational support as employees' perception that their organization values their contribution and well-being.
11.	(Rhoades and Eisenberger, 2002)	Perceived Organizational Support: A Review of the Literature	Reviews antecedents and consequences of POS	70+ studies	Review	Links organizational support with job attitudes, commitment, performance and withdrawal-related outcomes.
12.	(Brod, 1984)	Technostress: The Human Cost of the Computer Revolution	Establishes the foundational concept of technostress	Conceptual	Foundational book	Provides an early conceptual basis for understanding stress associated with workplace technology.
13.	(Tarafdar et al., 2015)	Technostress: Negative effect on performance and possible mitigations	Examines negative effects of technostress and possible mitigation mechanisms	237 institutional sales professionals	Empirical	Technostress creators were associated with poorer performance; competence and organizational mechanisms were considered potential mitigators.
14.	(Sharma and Tiwari, 2023)	Modeling the impact of techno-stress and burnout on	Examines techno-stress, burnout, WLB and turnover intention	528 Indian IT employees	Time-lagged empirical study	Connects techno-stress and burnout with employee

		employees' work-life balance and turnover intention: A job demands-resources theory perspective				outcomes including turnover intention within a JD-R perspective.
15.	(Sharma et al., 2023)	Examining the nexus between technostress and turnover intention: the moderating influence of PsyCap in Indian information management contexts	Examines technostress and turnover intention	544 Indian IT employees	Time-lagged, PLS-SEM	Reports a relationship between technostress and turnover intention, with work exhaustion and PsyCap considered in the model.
16.	(Wankhede and Khandelwal, 2026)	A systematic review of AI induced technostress and human resource development interventions	Reviews AI-induced technostress and HRD interventions	36 included studies	Systematic review	Identifies AI-related technostress dimensions such as overload, complexity, insecurity and uncertainty, and discusses training/support interventions.
17.	(Zhang et al., 2025)	Anxiety or engaged? Research on the impact of technostress on employees' innovative behavior in the era of artificial intelligence	Examines technostress and employee responses in the AI era	Employees	Empirical	Examines pathways involving technostress, job anxiety, work engagement and innovative behavior in AI-enabled work.
18.	(Kumar et al., 2026)	Are AI and robots the real reason people quit their jobs? Connecting AI awareness, technostress and organizational support in Indian workplaces	Examines AI awareness, technostress, organizational support and turnover	476 Indian service/manufacturing employees	Empirical	Directly connects AI/robotics awareness and technostress with turnover-related outcomes and considers organizational support.

19.	(Tett and Meyer, 1993)	Job Satisfaction, Organizational Commitment, Turnover Intention, and Turnover: Path Analyses Based on Meta-Analytic Findings	Examines relationships among job attitudes, turnover intention and turnover	155 studies / 178 independent samples	Meta-analysis	Establishes turnover intention as an important turnover-related outcome and examines its relationship with satisfaction and commitment.
20.	(Chuang et al., 2025)	Insights from the Job Demands–Resources Model: AI's dual impact on employees' work and life well-being	Examines AI-related demands/resources and employee well-being	Employees working with AI	Empirical	Shows the dual nature of AI: AI-related technostress can contribute to exhaustion and work-family conflict, while AI efficacy/productivity-related resources may have beneficial effects.
21.	(Pham et al., 2026)	Technostress and work engagement in the ICT industry: the role of work–life balance and employee moonlighting	Examines technostress, WLB and work engagement	354 Vietnamese ICT employees	Empirical	Technostress dimensions were associated with lower work engagement, partly through work-life balance.
22.	(Ruan et al., 2026)	Trust in AI decision support systems relates to innovation and technostress through empowerment and dependency pathways	Examines AI-DSS, trust, technostress and organizational AI support	452 AI-DSS users / knowledge workers	Empirical	Connects AI-system use with technostress through dependency and examines AI literacy and organizational AI support as contextual factors.
23.	(Sathish and Indradevi, 2026)	Competing strain and resource pathways linking AI-ena-	Examines AI-enabled work, digital intensity, technostress and organizational support	516 Indian IT employees	Empirical, PLS-SEM	Examines technostress as a strain pathway and perceived organizational

		bled work systems to employee wellbeing				support as a potential resource in AI-enabled work.
24.	(Jin et al., 2026)	Understanding AI Technostress and Employee Career Growth from a Socio-Technical Systems Perspective: A Dual-Path Model	Examines AI technostress and employee career growth	Employee–supervisor pairs	Empirical	Examines challenge and hindrance pathways of AI technostress and the role of organizational AI support.
25.	(Zhang et al., 2026)	How artificial intelligence (AI) usage affects employees' workplace well-being: a job demands-resources perspective	Examines AI usage as a job demand and resource	366 Chinese employees using AI	Three-wave empirical study	Shows that AI usage can operate through both resource and demand pathways, including autonomy and job insecurity.

Table 2: Represents characteristics of the included studies

The publications included in this review addressed complementary facets of the topic, encompassing foundational research on technostress and job demands–resources theory, as well as recent findings regarding AI-enabled work environments. Earlier studies predominantly established connections between technology-related demands, technostress, and employee outcomes, while more recent studies have expanded these connections to include AI usage, AI-related work demands, and organizational support.

Use of AI at work: The increasing use of artificial intelligence (AI) has transformed workplace activities by integrating AI-powered tools, machine learning, and data-driven applications into organizational processes. AI is being used to support workplace activities and employee tasks, enabling organizations to improve productivity, process information, and support decision-making (Chuang et al., 2025; Zhang et al., 2026). AI-enabled systems can also support employees by improving job autonomy and productivity and by facilitating more data-driven work processes (Chuang et al., 2025; Zhang et al., 2026). However, the increasing integration of AI also changes employees' work environments and may require them to adapt to new systems, develop technological competencies, and manage changing work requirements. Concerns regarding job insecurity, technostress, and the changing nature of work may further influence employees' experiences and perceptions of AI-enabled work environments (Zhang et al., 2026; Kumar et al., 2026). Thus, AI adoption should be considered not only in terms of organizational efficiency but also in relation to the new technological demands placed on employees.

Lack of technological Competence: The increasing use of AI and other digital technologies has increased the need for employees to develop the technological competencies required to perform their work effectively. However, employees differ in their prior experience and exposure to technology, which may create gaps in their ability to adapt to new systems. Employees with lower technological readiness may experience difficulties in managing technology-based tasks, lower self-efficacy, and greater dependence on technical assistance (Ragu-Nathan et al., 2008). Similarly, technological complexity has been identified as an important workplace stressor, as difficulty in understanding and using technology can increase mental fatigue and performance-related strain (Ayyagari et al., 2011). Technological competence is therefore important for employees' ability to cope with changing work requirements. Where employees lack the necessary skills, they may require additional time to understand systems, resolve technical problems, and seek assistance, potentially affecting their work performance (Tarafdar et al., 2007).

This suggests that gaps between employees' technological competencies and the demands of AI-enabled work may contribute to greater difficulty in adapting to technological change and may increase the potential for technostress.

AI related workload: The increasing use of AI and digital technologies can change the pace and volume of work by requiring employees to process more information, manage multiple technology-enabled tasks, and adapt to changing work requirements. Technology overload has been identified as an important technology-related demand, particularly when employees are required to handle more information and technological tasks than they can effectively manage (Ayyagari et al., 2011; Karr-Wisniewski and Lu, 2010). Similarly, technology-related work demands can increase the pressure on employees to respond continuously to changing technological requirements, thereby contributing to strain in the workplace (Tarafdar et al., 2007). Recent research further indicates that technology-related demands remain relevant in contemporary AI-enabled work environments, where employees may need to continuously adapt to new systems and changing work processes. Such demands can increase employees' cognitive and psychological burden when adequate resources are not available to manage them. Therefore, AI-related workload can be considered an important work demand that may contribute to employee technostress, particularly when the pace and complexity of technological change exceed employees' available resources.

Technostress: Technostress refers to the strain employees experience when they find it difficult to cope with technology-related demands in the workplace. The concept was introduced by Brod (1984), who described technostress as a condition associated with difficulties in adapting to computer technologies. Later research established that technology-related demands can arise from factors such as overload, complexity, uncertainty, and insecurity (Tarafdar et al., 2007; Ayyagari et al., 2011). These dimensions are particularly relevant in AI-enabled workplaces, where employees may need to continuously learn, adapt to evolving systems, and manage changing technological requirements. The major five dimensions of technostress identified in previous research (Tarafdar et al., 2007; Ragu-Nathan et al., 2008):

- **Techno-overload:** technology increases the pace or volume of work.
- **Techno-invasion:** technology extends work into employee's personal lives.
- **Techno-complexity:** employees perceive technology as difficult to understand or use.
- **Techno-uncertainty:** continuous technological changes require employees to repeatedly learn and adapt.
- **Techno-insecurity:** employees are concerned that technological change may threaten their job security.

From a Job Demands–Resources (JD-R) perspective, technology-related demands can consume employees' psychological resources when adequate resources are not available to manage them (Bakker and Demerouti, 2007). In this context, technostress provides a potential mechanism through which AI-related workload and technological competence challenges may influence employee outcomes. Employees who face excessive technological demands or feel inadequately prepared to use new systems may experience greater strain, which can subsequently affect their work-related attitudes and outcomes. Recent research has extended this relationship to AI-enabled work environments. For example, Sharma and Tiwari (2023) and Sharma et al. (2023) examined technostress in relation to employee outcomes in technology-intensive workplaces, including turnover intention. Similarly, recent AI-focused studies have examined how AI-related technological demands and support shape employees' experiences of technostress (Kumar et al., 2026; Jin et al., 2026; Ruan et al., 2026). Thus, technostress represents a central mechanism in the present review for understanding how changing AI-related work demands may translate into adverse employee outcomes.

Turnover Intention: Turnover intention refers to an employee's conscious intention to leave their current job (Tett and Meyer, 1993). It is considered an important indicator of potential employee turnover and represents a withdrawal response that may develop before actual resignation. In technology-intensive work environments, employees experiencing high levels of technostress may find technological demands increasingly difficult to manage. Previous research has linked technostress with turnover intention, suggesting that technology-related demands such as overload and complexity can contribute to employees' intention to leave (Ragu-Nathan et al., 2008; Sharma and Tiwari, 2023; Sharma et al., 2023). From a JD-R perspective, when job demands remain high without adequate resources, employees may experience strain and disengagement, which can contribute to withdrawal intentions (Bakker and Demerouti, 2007). The reviewed literature also indicates that organizational support may influence this relationship. Training, technical assistance, and access to relevant resources can help employees manage technology-related demands and reduce the strain associated with technological change. Thus, in the proposed framework,

technostress is positioned as a link between AI-related work demands and turnover intention, while AI-Specific Organizational Support is considered a contextual resource that may help reduce these negative effects.

AI Specific organizational support: AI-Specific Organizational Support (AI-SOS) refers to the organizational, technical, and psychological support provided to employees to help them manage AI-related work demands. This support may include AI-related training, technical assistance, guidance, knowledge resources, and opportunities to develop the skills required to adapt to AI-enabled work. The concept is supported by Perceived Organizational Support (POS), which suggests that employees develop perceptions about the extent to which their organization values their contributions and cares about their well-being (Eisenberger et al., 1986; Rhoades and Eisenberger, 2002). From the JD-R perspective, organizational support functions as a job resource that can help employees cope with demanding work conditions and protect them from excessive strain (Demerouti et al., 2001; Bakker and Demerouti, 2007). In the context of AI-enabled work, this support becomes particularly important because employees may face new learning requirements, changing work processes, and increased technological demands. Providing appropriate training, technical guidance, and resources can help employees develop confidence and competence in using AI, making AI-related demands easier to manage. In this way, organizational support may reduce the strain associated with technological change rather than allowing AI-related demands to develop into higher levels of technostress. Accordingly, the present review positions AI-SOS as a potential protective resource within the proposed framework. Rather than treating technostress as an unavoidable consequence of AI adoption, the framework proposes that the level of organizational support may influence how employees experience and respond to AI-related demands. Adequate AI-SOS may therefore help reduce technostress and potentially weaken its negative effect on turnover intention, whereas limited support may leave employees less prepared to cope with technological demands. This positioning of AI-SOS as a contextual resource highlights its importance in understanding how organizations can support employees during AI-driven workplace change.

The Proposed Conceptual Framework presented in Figure 2:

Interpretation of Conceptual Framework: The proposed framework elucidates how AI-related transformations in the workplace may influence employees' intentions to leave through the lens of technostress. The utilization of AI at work, AI related workload, and technological competence related challenges constitute significant work demands that may increase employees' experiences of technostress. An increase in technostress may subsequently lead to heightened turnover intention, as employees encounter greater difficulties in adapting to evolving technological requirements. Furthermore, the framework situates AI-Specific Organizational Support (AI-SOS) as a contextual and protective resource. Support in the form of AI-related training, technical assistance, and pertinent resources may aid employees in managing these demands, alleviating the strain linked to AI, and potentially mitigating the negative correlation between technostress and turnover intention. Consequently, the framework integrates the demand–strain–outcome pathway while emphasizing organizational support as a viable mechanism for alleviating the detrimental effects of AI-enabled work on employees.

PROPOSED HYPOTHESIS

H1: Use of AI at work is positively associated with technostress among employees

H2: Lack of technological competence is positively associated with technostress among employees

H3: AI-related workload is positively associated with technostress among employees

H4: Technostress is positively associated with employee turnover intention

H5: AI-Specific Organizational Support weakens the positive relationship between technostress and employee turnover intention

RESEARCH GAPS

The reviewed literature highlights several gaps in understanding employee responses to AI-enabled work. Earlier technostress research has largely focused on general information technologies, with comparatively limited attention to the specific work demands associated with AI (Tarafdar et al., 2007; Ayyagari et al., 2011; Wankhede and Khandelwal, 2026). In particular, the combined influence of AI-related workload and technological competence challenges on employee technostress remains insufficiently examined. A further gap concerns the relationship between AI-related technostress and turnover intention. Although

previous studies have established a relationship between technostress and turnover intention in technology-intensive workplaces (Ragu-Nathan et al., 2008; Sharma and Tiwari, 2023; Sharma et al., 2023), limited research has examined this relationship specifically through AI-related work demands**.** Most importantly, the reviewed literature indicates limited attention to AI-Specific Organizational Support (AI-SOS) as a distinct resource for managing AI-related technostress. Existing research establishes the importance of organizational support in helping employees cope with demanding work conditions (Eisenberger et al., 1986; Rhoades and Eisenberger, 2002; Bakker and Demerouti, 2007), but its AI-specific role in reducing technostress and potentially buffering its effect on turnover intention remains underexplored. This gap provides the basis for positioning AI-SOS as a protective contextual resource in the proposed framework and highlights the need for future empirical research to examine this relationship directly.

FURTHER SCOPE OF THE RESEARCH

The proposed framework provides several directions for future research. First, longitudinal studies can examine how technostress develops and changes over time, helping to distinguish between temporary adjustment and persistent technological strain. Second, the framework can be tested across different industries and organizational sizes, such as IT, healthcare, and mid-sized organizations, to examine whether AI-related demands produce similar employee outcomes across contexts. Future research can also examine how different types of AI systems and their characteristics, including complexity and perceived fairness, influence employees' experiences of technostress. Finally, future studies can explore additional organizational and managerial factors that may influence the relationship between AI-related demands, technostress, and turnover intention, including different management and support strategies.

REPORTING BIAS AND CERTAINTY OF EVIDENCE

The potential for reporting bias arising from missing or selectively reported results was evaluated in accordance with the PRISMA guidelines. The researcher examined the available findings pertinent to the review objectives and assessed whether significant results seemed to be absent or selectively reported. No formal reporting-bias tools, funnel plots, or statistical tests were employed. Additionally, no authors were contacted for supplementary information, and no publications were excluded solely due to suspected reporting bias. The lack of a standardized reporting-bias assessment is recognized as a limitation of this review.

The certainty of the available evidence was qualitatively assessed across the 25 included publications, taking into account methodological quality, consistency of findings, and relevance to the review objectives. No formal framework for assessing certainty of evidence, such as GRADE, was utilized, and no standardized certainty ratings were provided. The findings were interpreted with caution, considering the variations in study designs and contexts. The absence of a formal assessment of certainty is acknowledged as a limitation of this review.

CONCLUSION

This systematic review emphasizes that work enhanced by AI can create new demands concerning workload, technological proficiency, and adaptability, which may lead to technostress and an increased intention to leave the organization. Furthermore, it suggests the introduction of AI-Specific Organizational Support (AI-SOS) as a contextual resource that may assist employees in managing these demands and mitigating the adverse effects of technostress. Overall, the review underscores the importance of balancing AI adoption with employee support and well-being. Future research should empirically investigate these relationships across various workplace contexts, particularly focusing on the potential role of AI-SOS.

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CONTRIBUTION OF AUTHORS

Ritika PANCHAL directed the comprehensive development of the study from its inception to its completion. She identified and refined the research topic, conducted a thorough literature search, reviewed and evaluated relevant publications, developed the conceptual framework, proposed relationships, synthesized and interpreted the evidence, and prepared the manuscript from its initial draft to the final version. Additionally, she prepared the tables and conceptual framework, coordinated the overall development of the manuscript, incorporated revisions, and presented the work at the conference. **Pankaj SAINI, Ritika MALIK, Megha SEHGAL, Romita MODI, S. B. SAWANT, and Neelam SHARMA** authors offered academic and methodological guidance throughout the study's development, reviewed the relevant literature and manuscript, contributed feedback regarding the relevance, interpretation, and presentation of the findings, and provided critical comments and revisions. All authors reviewed and approved the final manuscript and consented to be accountable for the accuracy and integrity of the work.

CONFLICT OF INTEREST

The authors affirm that they possess no competing interests or financial or professional relationships that may have impacted the conduct, interpretation, or reporting of this study.

ETHICAL STATEMENT

Ethical approval was not necessary for this study, as it relied solely on previously published literature and did not involve human participants, primary data collection, or access to personal or identifiable information.

DATA AVAILABILITY

The data and information supporting the findings of this systematic review are sourced from the previously published literature incorporated within the review. The essential information extracted from the included publications is detailed in the manuscript and the accompanying tables. No new primary dataset was generated or collected during this study.

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FIGURE LEGENDS

Figure 1: PRISMA 2020 flow diagram: Figure 1 illustrates the progression of publications through the stages of identification, screening, eligibility assessment, and inclusion in the systematic review.

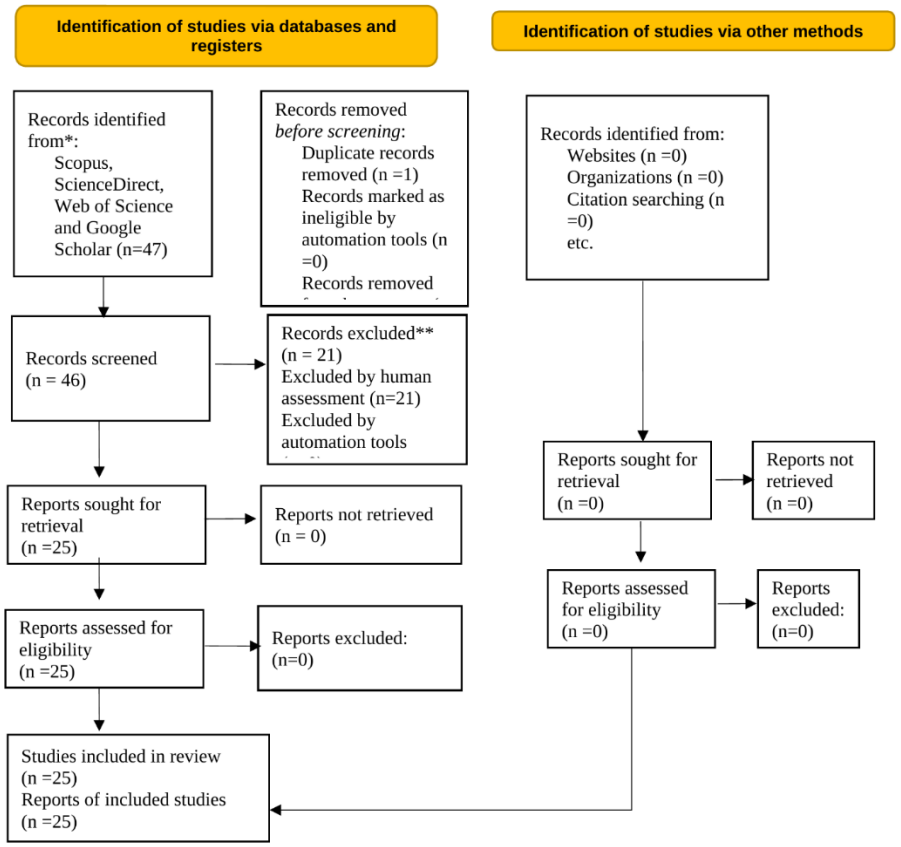


Figure 2: Proposed conceptual framework: Based on the synthesis of the reviewed literature, a proposed conceptual framework was developed to illustrate the relationships among AI-related work demands, technostress, turnover intention, and AI-Specific Organizational Support (AI-SOS).

