

A Systematic Literature Review of Technostress Classification in Generative AI Interactions Using Behavioral Proxies

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ABSTRACT

The rapid adoption of generative artificial intelligence (AI) has amplified concerns regarding technostress, cognitive load, and related affective states. While traditional stress assessment relies heavily on subjective surveys, there is a growing need for computational frameworks that can classify technostress-related cognitive and affective states using behavioral proxies. This study presents a Systematic Literature Review (SLR) following the PRISMA protocol to examine recent literature (2020–2026) on supervised learning approaches for technostress-related classification in generative AI and AI-assisted interaction contexts. The synthesis indicates that multimodal behavioral inputs including keystroke dynamics, mouse movements, prompt iteration behavior, and gaze tracking are often associated with stronger classification performance than unimodal systems. In addition, within the reviewed literature, Random Forests and ensemble-based strategies are frequently reported as strong performers in technostress-related classification tasks. Despite these advances, the review identifies persistent challenges related to cross-contextual generalizability, real-time adaptation, and the need for Explainable AI (XAI) in sensitive domains. Based on these findings, the paper proposes a human-centered adaptive conceptual framework that integrates behavioral signals, classification models, explainability, and real-time adaptation for future algorithmic stress classification.



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I. INTRODUCTION

The proliferation of generative artificial intelligence (AI) in work, education, and daily life has intensified concerns about technostress, cognitive load, and specific affective states, such as fatigue and digital exhaustion [1]–[5]. While AI-assisted environments offer significant productivity gains, continuous interaction with highly complex generative systems introduces new psychological challenges. Technostress is linked to negative psychological, behavioral, and organizational outcomes, but it also presents nuanced effects depending on context and user perception [4]–[6]. Traditionally, the evaluation of cognitive workload relies heavily on subjective measurements, such as self-reported surveys. However, these retrospective methods fail to capture real-time affective states. Consequently, there is a critical need for robust algorithmic frameworks to classify

technostress-related cognitive and affective states in generative AI interactions using objective human behavioral data.

Recent advancements in machine learning have catalyzed a necessary shift from purely psychological evaluations to automated computational classification approaches. Current literature indicates that supervised learning models ranging from Support Vector Machines (SVM) and Random Forests to advanced deep learning architectures are increasingly utilized to classify technostress-related states, digital exhaustion, and cognitive overload [7]–[9]. Furthermore, research demonstrates that multimodal approaches combining behavioral signals (e.g., keystroke dynamics, mouse movements) with physiological or computer vision data yield higher classification performance accuracy than unimodal systems [9], [10].

Despite this progress, the existing literature spans heterogeneous contexts, including general IT environments, human-computer interaction (HCI), workplace settings, and emerging generative AI applications, making it difficult to establish a focused understanding of behavioral proxies for technostress-related classification in generative AI interactions [9], [11]. Furthermore, behavioral interaction data do not measure stress directly, but rather serve as behavioral proxies. The reviewed studies also use heterogeneous ground-truth and labeling procedures, which may affect labeling consistency and cross-study comparability.

To bridge these theoretical and methodological gaps, this study presents a Systematic Literature Review (SLR) to examine recent literature spanning 2020–2026 on supervised learning approaches for classifying technostress and related cognitive states from behavioral proxies in AI-assisted environments. This specific timeframe was selected to capture the computational advancements following the massive deployment of large-scale generative AI models. This study contributes a structured synthesis of how human behavioral signals are transformed into algorithmic proxies for technostress-related classification in generative AI interactions. Beyond synthesizing input features and classification algorithms, the novelty of this review lies in proposing a human-centered adaptive conceptual framework. This framework conceptualizes the integration of behavioral sensing, multimodal classification, and explainable decision support (XAI) to prioritize transparency, address ethical concerns, and enable real-time adaptation [11].

To address the aforementioned gaps, this systematic literature review aims to answer the following research questions:

- RQ1: What behavioral modalities are used as input features for technostress-related classification in generative AI interactions?
- RQ2: Which classification approaches show the strongest reported performance and interpretability for technostress-related cognitive-state classification?
- RQ3: What methodological and ethical challenges limit the deployment of computational approaches for technostress classification in real-world AI environments?

II. THEORETICAL BACKGROUND

A. Key Concepts

To ensure conceptual clarity, this study distinguishes three related but non-equivalent constructs. Cognitive load refers to the mental processing demands imposed by a task, particularly the burden placed on working memory. Affective states refer to transient emotional responses, such as frustration or anxiety, that may accompany technology use. Technostress refers to negative psychological and behavioral responses arising from demands associated with the use of technology. In the context of generative AI, these

constructs are treated as related but conceptually distinct outcomes rather than interchangeable terms [1]–[3], [5], [7], [12]–[14]. To computationally evaluate these internal states, classification algorithms utilize behavioral signals such as keystroke dynamics, erratic mouse movements, and gaze variations as observable behavioral proxies [7], [9], [10], [15], [16]. By translating subjective distress into measurable data [7], [9], these classification approaches complement retrospective surveys to enhance overall detection performance, despite persistent challenges in model explainability and cross-contextual generalizability [9], [11].

B. Affective Computing and XAI

Affective computing bridges human psychology and machine intelligence [11], providing the computational mechanism to transform observable interaction behaviors into measurable indicators of cognitive overload and fatigue [9], [10]. State-of-the-art models leverage multimodal affect recognition by integrating keystroke dynamics, mouse movements, gaze, and computer vision data [9], [10], [16] to achieve significantly stronger classification performance than unimodal approaches [9], [16].

To formulate this mathematically, if the extracted multimodal behavioral features are represented as a vector $x = [x_1, x_2, \dots, x_M]^T \in \mathcal{X}$, where each x_i represents a standardized metric from keystroke, mouse, gaze, or linguistic logs. The classification task is to learn a mapping function $f: \mathcal{X} \rightarrow \mathcal{Y}$, where $\mathcal{Y} = \{y_1, y_2, \dots, y_K\}$ represents the discrete cognitive states (e.g., $y \in \{\text{Relaxed}, \text{Fatigue}, \text{Overload}\}$). In deep learning models, the classification probability is represented as:

$$P(y = c | x) = \frac{e^{w_c^T h + b_c}}{\sum_{j=1}^K e^{w_j^T h + b_j}} \quad (1)$$

where h is the latent feature representation and w_c, b_c are the classification parameters for class c .

However, deploying advanced deep neural networks introduces an opaque “black-box” problem, necessitating Explainable AI (XAI) [11]. To resolve the “black-box” trade-off, XAI frameworks ensure transparency and trustworthiness by elucidating which specific behavioral features (e.g., erratic cursor movements, response latency, or rapid prompt iterations) most significantly drive the cognitive overload classification of cognitive overload. Explainable models like SHAP (Shapley Additive Explanations) approximate the complex model $f(x)$ with a linear explanation model $g(z')$:

$$g(z') = \phi_0 + \sum_{i=1}^M \phi_i z'_i \quad (2)$$

where $z' \in \{0,1\}^M$ is a binary coalition vector indicating feature presence, and $\phi_i \in \mathbb{R}$ is the Shapley value denoting the feature contribution.

$$\phi_i(f, x) = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|! (|F| - |S| - 1)!}{|F|!} [f_x(S \cup \{i\}) - f_x(S)] \quad (3)$$

where F is the set of all features, S is a subset of features excluding feature i , and $f_x(S)$ is the conditional expectation of the model prediction given the subset S [7], [10], [11].

C. Conceptual Framework

This review's conceptual framework integrates psychological stress theories with computational classification mechanisms [1], [2], [11]. Drawing from the Technostress Framework and Cognitive Load Theory, we elucidate how generative AI's dense processing demands act as primary stressors inducing cognitive overload [1], [12]. Rather than relying on subjective perceptions, this framework posits that internal distress invariably manifests as observable behavioral signals (e.g., keystroke dynamics, mouse movements, gaze) [7], [10], enabling computational models to infer latent affective states [9], [10]. To bridge this gap, Affective Computing serves as the core algorithmic methodology [11]. By processing these heterogeneous multimodal features, classification algorithms generate computational classifications or predictions of cognitive overload, fatigue, and digital exhaustion [9], [16]. Crucially, integrating Explainable AI (XAI) ensures these predictions remain transparent, interpretable, and ethically accountable [11]. As illustrated in Fig. 1, this continuous flow from AI-induced technological stimuli to behavioral manifestations and human-centered algorithmic classification forms the foundational lens for the subsequent literature synthesis.

III. METHODOLOGY

A. Search Strategy and Corpus Definition

Adhering to PRISMA guidelines, a systematic search was conducted on May 10, 2026, across three sources: Scopus, ScienceDirect, and Google Scholar. The search string, detailed in Table I, was constructed using Boolean operators connecting three thematic clusters: psychological and cognitive states (including technostress, cognitive load, cognitive overload, digital exhaustion, and related fatigue terms), technology context (including generative AI, artificial intelligence, and human-computer interaction), and computational approaches (including affective computing, behavioral signals, machine learning, and explainable AI). The search covered studies published from January 2020 to May 2026 to capture recent computational developments during the period in which large-scale generative AI systems became increasingly prominent. The initial search returned 310 records, comprising 108 records from Scopus, 142 from

Google Scholar, and 60 from ScienceDirect. The 31 studies that remained after screening and eligibility assessment were subsequently stratified into a computational Core Corpus, consisting of studies providing empirical evidence on supervised machine learning using behavioral proxies, and a Supporting Corpus, consisting of studies used to contextualize psychological and cognitive mechanisms, affective states, and ethical or explainability considerations.

The conceptual framework presented in Figure 1 also guided the literature search and selection process. Specifically, the framework was used to define the major thematic dimensions explored in this review, namely AI-induced technostress, behavioral sensing modalities, supervised classification approaches, and Explainable AI (XAI). These dimensions informed the development of the search keywords, database queries, and subsequent categorization of the retrieved studies, ensuring consistency between the theoretical foundation and the systematic review methodology.

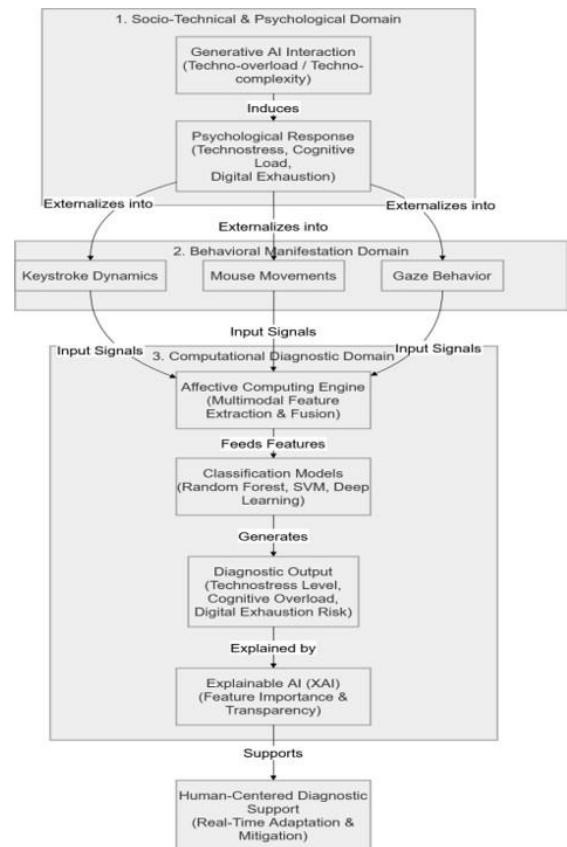


Figure 1. Conceptual Framework

B. Inclusion and Exclusion Criteria

To ensure methodological rigor, reproducibility, and direct alignment with the research questions, explicit inclusion and exclusion criteria were established prior to the screening process. These parameters prioritize high-quality, peer-reviewed computational studies that

implement algorithmic classification approaches using behavioral signals, while systematically filtering out purely clinical or non-empirical literature. To guarantee reproducibility, the exact Boolean search string, alongside the specific selection parameters, is comprehensively detailed in Table I.

C. Data Selection Process

The study selection process followed the PRISMA workflow presented in Fig. 2. During the identification phase, 310 records were retrieved from the three search sources, and 80 duplicate records were removed before screening. The remaining 230 unique records were screened based on their titles and abstracts, resulting in 150 records being excluded because they did not meet the predefined scope, including records outside the 2020–2026 publication period, non-peer-reviewed or non-English records, and records insufficiently related to technostress, cognitive states, or computational approaches. A total of 80 reports were subsequently sought for retrieval, of which 10 reports could not be retrieved because the full text was not accessible. The remaining 70 full-text reports were assessed for eligibility. Of these, 39 reports were excluded: 15 lacked an explicit machine learning implementation or behavioral component, 14 relied exclusively on physiological sensors without behavioral proxies, and 10 fell outside the predefined Generative AI or technostress scope. The final 31 studies were included in the review and subsequently stratified into the computational Core Corpus and the Supporting Corpus.

Quality Assessment and Risk of Bias A structured Quality Assessment (QA) protocol was applied to the Core Corpus to evaluate the methodological reliability and potential sources of bias in the computational studies. The assessment examined dataset size, ground-truth or labeling procedures, data-splitting strategies, validation protocols, subject independence, evaluation metrics, data-leakage risk, and the completeness of methodological reporting. Particular attention was given to whether studies used random train-test splitting or subject-independent validation, such as cross-user validation or Leave-One-Subject-Out procedures. Random splitting may introduce subject-related data leakage when observations from the same participant are distributed across both training and testing sets, potentially producing overly optimistic estimates of model performance. The QA also documented differences in ground-truth construction and evaluation metrics across studies. These differences were considered during synthesis to avoid treating performance values obtained under non-equivalent datasets, labeling procedures, validation protocols, and evaluation metrics as directly comparable. To operationalize this The defined quality-assessment criteria were systematically applied to the Core Corpus, and the resulting methodological

observations were incorporated into the synthesis and interpretation of the reviewed studies. to document these methodological dimensions for each study in the Core Corpus.

TABEL I
INCLUSION AND EXCLUSION CRITERIA WITH SEARCH STRING

Category	Description
Search String	("technostress" OR "cognitive load" OR "cognitive overload" OR "digital exhaustion" OR "zoom fatigue") AND ("generative AI" OR "artificial intelligence" OR "human-computer interaction") AND ("affective computing" OR "behavioral signals" OR "machine learning" OR "explainable AI")
Inclusion Criteria	1. Population: Human participants, including HCI users, students, employees, or other users interacting with AI-assisted systems. 2. Technology Context: Generative AI applications or AI-assisted interaction contexts relevant to technostress, cognitive load, fatigue, or affective-state assessment. 3. Behavioral Signal: Uses observable behavioral proxies such as keystroke dynamics, mouse movements, gaze/eye-tracking, interaction logs, or conversational/prompt behavior. 4. Algorithm: Employs supervised machine learning or deep learning methods for classification, detection, prediction, or related computational assessment. 5. Outcome: Evaluates technostress, cognitive load, cognitive overload, fatigue, or specified affective states. 6. Study Design: Peer-reviewed empirical studies published in English between January 2020 and May 2026 that report sufficient methodological information for synthesis.
Exclusion Criteria	1. Publication Type: Preprints, extended abstracts, non-peer-reviewed publications, or non-English publications. 2. Research Scope: Studies outside the predefined technostress/cognitive-state and AI/Generative AI scope. 3. Methodological Scope: Studies without a relevant machine learning or deep learning implementation.

	4. Behavioral Data: Studies relying exclusively on physiological sensors (e.g., EEG or ECG) without behavioral proxy data. 5. Outcome: Studies that do not evaluate technostress, cognitive load, cognitive overload, fatigue, or relevant affective states.
Quality Requirement	Must report sufficient methodological information, including dataset characteristics, ground-truth labeling, validation protocol, and evaluation metrics to enable quality assessment and comparative synthesis.

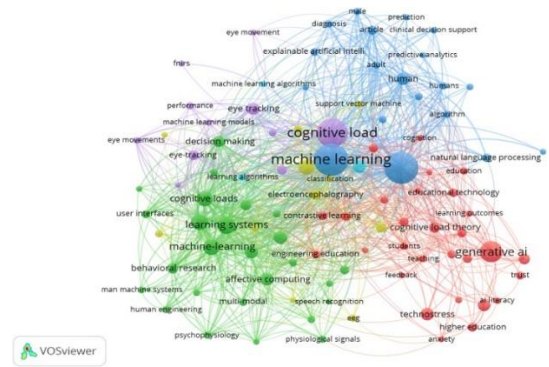


Figure 3. Bibliometric network of AI-induced technostress diagnostics

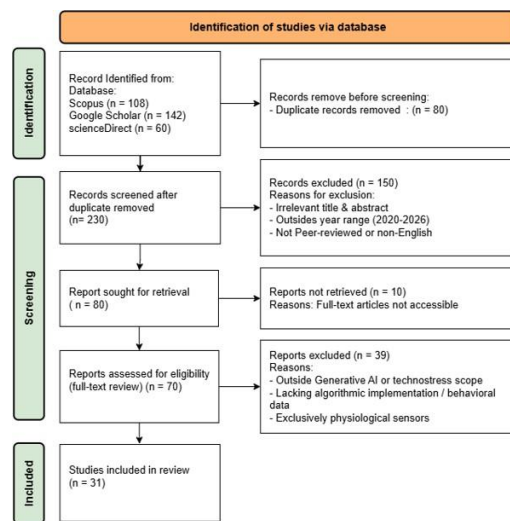


Figure 2. PRISMA Flow Diagram

D. Data Extraction, Synthesis, and Bibliometric Mapping

A structured extraction protocol applied exclusively to the Core Corpus captured metadata, target cognitive/affective states, behavioral modalities, algorithmic architectures, per-formance metrics, and XAI integration. To complement this robust manual thematic synthesis, VOSviewer mapped the domain’s intellectual structure via keyword co-occurrence analysis. Crucially, VOSviewer served strictly as a supplementary visualization tool; all primary findings and algorithmic evaluations derived fundamentally from manual qualitative synthesis to ensure accurate interpretation of computational mechanics rather than relying on automated clustering.

IV. RESULT

A. Characteristics of the Literature

Following the systematic selection process, a final corpus of 31 studies was established. The literature exhibits a sharp publication surge between 2020 and 2026, reflecting a critical academic pivot toward quantifying AI-induced technostress and cognitive overload. To visualize this intellectual structure, a VOSviewer keyword co-occurrence analysis was executed (Fig. 3). The network reveals three distinct thematic clusters that directly validate our conceptual framework: a contextual cluster highlighting socio-technical stressors (e.g., “generative AI,” “technostress,” “anxiety”); a behavioral modality cluster centered on “affective computing,” “multi-modal” inputs, and “psychophysiology”; and a computational classification cluster driven by dominant nodes for “machine learning,” “cognitive load,” and “prediction.” This tri-cluster topology visually confirms the active convergence of psychology and computer science into a cohesive, multidisciplinary classification research domain.

B. Characteristics of the Literature

Addressing the primary research questions, the extracted data is synthesized across two thematic dimensions (summa-rized in Table II):

- 1) **Theme 1: Human Behavioral Input Modalities:** Recent frameworks pivot from subjective self-reporting to extracting cognitive friction via continuous, unobtrusive interaction data. Keystroke and mouse dynamics serve as foundational indicators of motor-cognitive exhaustion [17], [18]. Beyond physical peripherals, computer vision (eye-tracking, pupil dilation, facial action units) provides high-fidelity cognitive load proxies [13], [19]. Additionally, linguistic data and prompt iterations from GenAI chat logs are emerging as novel stress predictors [8], [20]. In generative AI environments, specific interaction

features such as prompt length, semantic similarity between sequential prompts, prompt revision rate, and text regeneration frequency serve as direct behavioral proxies for cognitive friction and frustration. These modalities are consistently contextualized via temporal features like response latency [13].

- 2) Theme 2: Algorithms and Classification Performance: Classification modeling within the reviewed literature is predominantly driven by supervised learning, with Support Vector Machines (SVM) and Random Forests (RF) serving as prevalent baseline classifiers [11], [13]. The reviewed studies also employ ensemble learning, deep learning architectures (e.g., CNNs and RNNs), and fuzzy-optimized models to address increasingly complex behavioral classification tasks [8], [12], [21]. Although reported performance values range from approximately 70% to over 99%, direct algorithmic ranking across studies is methodologically inappropriate because the reported results were obtained using heterogeneous datasets, behavioral modalities, ground-truth labeling procedures, validation strategies, and evaluation metrics. In particular, Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC) quantify different aspects of classification performance and therefore should not be interpreted as directly comparable across independent studies. Furthermore, the choice of validation protocol substantially influences performance interpretation. Subject-independent validation approaches, such as Leave-One-Subject-Out cross-validation, provide a more rigorous assessment of cross-subject generalizability, whereas random train-test splits may increase the risk of subject-related data leakage when correlated behavioral observations from the same participant are distributed across both training and testing sets. Finally, as increasingly complex classification models are adopted, the reviewed literature also highlights the growing integration of Explainable AI (XAI) techniques, such as SHAP, to improve model interpretability, feature transparency, and trustworthiness in behavioral classification systems [5], [18]. The comparative characteristics of the principal classification approaches identified in the reviewed studies are summarized in Table II, with emphasis on their typical application contexts, interpretability characteristics, strengths, and methodological limitations rather than direct cross-study performance ranking.

TABEL II
COMPARISON OF CLASSIFICATION ALGORITHMS FOR TECH-NOSTRESS CLASSIFICATION

Algorithm Family	Typical Application Context	Interpretability & XAI	Key Strengths	Key Limitations
Support Vector Machines (SVM)	Small-sample, high-dimensional data	Medium (Linear/RBF kernel)	Effective in high-dimensional small-sample spaces.	Sensitive to kernel and parameter tuning.
Random Forest (RF)	Tabular and behavioral features	High (SHAP/Feature Importance)	Robust to overfitting, handles heterogeneous tabular data.	Struggles with unstructured temporal sequences.
Deep Learning (CNN/LSTM)	Complex, temporal, or unstructured data	Low (Black-box, requires SHAP/LIME)	Automatically extracts spatial/temporal features.	Requires high compute, large training corpora.
Ensemble Methods	Heterogeneous or multimodal data	Medium-High (model-dependent)	Combines weak learners to minimize variance and bias.	High architectural complexity and latency.

V. DISCUSSION

A. Critical Synthesis

The synthesis indicates that multimodal approaches can capture the multidimensionality of AI-induced technostress more comprehensively than unimodal approaches by integrating complementary behavioral modalities, including motor-cognitive signals (e.g., keystroke dynamics and mouse movements) and autonomic indicators (e.g., eye-tracking and heart rate variability), thereby providing richer representations of user interaction patterns [3], [17], [18], [25], [29], [30]. Nevertheless, the review also identified considerable methodological heterogeneity across the included studies, particularly regarding validation strategies and evaluation protocols, which limits direct comparison of reported model performance. While several studies employed subject-independent validation to better estimate model generalizability, others relied on random train-test splits that may inadvertently distribute correlated behavioral observations from the same participant across both training and testing sets, increasing the potential risk of data leakage and overly optimistic performance estimates. Consequently,

validation strategy, data-splitting protocol, and reproducibility should be considered essential methodological quality indicators when interpreting classification performance and assessing the potential generalizability of behavioral machine learning models beyond the original study samples and controlled experimental settings [5], [8], [12], [18], [22], [30], [31].

These computational findings corroborate socio-technical evidence that cognitive load strongly mediates burnout and affective reactions during AI interaction [16], [23], [27]. As prolonged AI exposure is increasingly linked to digital exhaustion and broader mental health risks [1], [14], [21], [26], [29], [30]. Algorithmic classification approaches facilitate a vital shift from subjective surveys to real-time objective tracking. Ultimately, real-world deployment must rigorously balance predictive capabilities with ethical, privacy, and fairness imperatives. Continuous behavioral monitoring for technostress classification may involve sensitive information about user interactions, necessitating explicit informed consent and adherence to data minimization principles. Furthermore, automated classification models may be affected by differences in typing patterns, interaction styles, demographic characteristics, and cultural contexts, which can introduce

bias and compromise fairness. Because these systems rely on behavioral proxies rather than clinical biomarkers, their outputs should be interpreted as computational indicators of cognitive or affective states rather than definitive clinical determinations. This distinction is important for reducing the risk of overinterpretation, inappropriate intervention, and unwarranted workplace surveillance.

To further support the critical synthesis discussed above, Table III provides a representative synthesis of studies drawn from the Core and Supporting Corpora. The table distinguishes empirical computational studies used for the synthesis of behavioral proxies and classification approaches from theoretical, review, survey-based, and contextual studies used to support the interpretation of technostress, cognitive load, affective states, and explainability. This stratification helps clarify the different evidentiary roles of the reviewed studies and prevents contextual or theoretical sources from being interpreted as direct evidence of machine learning classification performance.

TABEL III
SYNTHESIS OF PRIOR STUDIES ON TECHNOSTRESS, BEHAVIORAL PROXIES, AND CLASSIFICATION APPROACHES

Study	Data Modalities	Classifiers/Methods	Methodological Focus	Key Contribution
[17]	Keystroke, Mouse Dynamics	SVM, Random Forest, Neural Networks	Behavioral dynamics logging	Demonstrated that peripheral interaction patterns reflect cognitive distress.
[22]	Physiological (EEG, ECG, GSR)	SVM, KNN, Random Forest, ANN	Multimodal sensor fusion	Showed physiological feature fusion yields robust affect classification.
[23]	Self-Report surveys	SEM (Structural Equation)	Cognitive load mediation	Modeled cognitive load as a predictor of technology continuance.
[13]	Eye-Tracking (Gaze, Pupil)	SVM, Random Forest	Ocular behavior metrics	Confirmed gaze tracking can differentiate high stress states.
[6]	Surveys, Platform Logs	Regression Analysis	Algorithmic control impact	Analyzed how algorithmic management induces stress in gig work.
[24]	Meta-Analysis / Review	N/A (Meta-Analysis)	Literature synthesis	Quantified negative psychological outcomes of technostress.
[25]	Conceptual Review	N/A (Conceptual)	Generative AI stressors	Identified risks and stressors specific to LLM and GenAI systems.
[18]	Mouse, Keyboard, ECG, GSR	Random Forest, Gradient Boost	Multi-source data fusion	Achieved high accuracy using non-invasive office behavior.
[16]	Survey Metrics	PLS-SEM, SVM	Technostress creators	Linked techno-overload and techno-invasion to student burnout.
[15]	Review of HCI Literature	N/A (Method Survey)	Worldload assessment metrics	Developed a taxonomy of workload measurements in HCI.
[7]	Conversational logs, Surveys	N/A (Qualitative)	AI Companion interactions	Evaluated chatbots' capability in recognizing psychological distress.
[4]	Survey Scales	Regression, PLS-SEM	AI adoption mediation	Shown that affect modulates AI adoption under technostress.
[3]	HRV (Heart Rate Variability)	Random Forest, SVM	Cardiac autonomic signals	Demonstrated Random Forest's robustness in HRV classification.
[11]	Surveys, Interaction Logs	SVM, Random Forest	Pandemic-era stress patterns	Evaluated Random Forest as superior to SVM for technostress.
[12]	Multimodal Logs	Fuzzy-Optimized RF (FOMRF)	Hybrid optimization models	Enhanced accuracy using fuzzy logic for boundary conditions.
[8]	Social Media / Text Logs	Stacked Ensemble, Meta-Learner	Linguistic affect mining	Used stacked meta-classifiers to capture technostress indicators.
[20]	Interaction Logs	RF, SVM, KNN	Baseline comparison study	Benchmarked RF against other traditional classifiers.
[26]	Survey Scales	Mediation Analysis (SEM)	Affective mediation pathways	Linked AI technostress directly to reduced quality of life.
[27]	Organizational Surveys	Structural Equation Modeling	Employee innovation outcomes	Revealed context-dependent effects of stress on innovation.
[14]	Academic Surveys	N/A (Review)	Academic fatigue & well-being	Synthesized student burnout risks from generative AI tools.
[21]	Multimodal logs, Ocular	Deep Learning (CNN/LSTM)	Sequential deep networks	Proved deep models excel in temporal stress pattern detection.

B. Theoretical Implications

This review advances socio-technical research by systematically bridging the traditional Technostress Framework with Affective Computing paradigms. While AI-induced stressors were historically evaluated via retrospective self-reporting [24], [25], Cognitive Load Theory (CLT) in HCI is fundamentally evolving from static surveys toward continuous, real-time algorithmic observation [13], [15]. The synthesized literature empirically validates that invisible psychological friction manifests directly as objectively quantifiable motor-cognitive and ocular anomalies [13], [17]–[19]. Furthermore, this review posits that algorithmic transparency via Explainable AI (XAI) is not merely a technical feature, but a

critical imperative that must be systematically integrated into core socio-technical theories governing human-AI trust and system adoption [5].

C. Practical Implications

This review offers critical directives for designing next-generation, human-centered generative AI. Moving beyond static classification approaches, a primary future direction is developing systems capable of real-time adaptation [17], [18]. Theoretically, when continuous multimodal classification models identify patterns associated with detect acute cognitive overload, future architectures should dynamically trigger mitigating interventions such as context-aware assistance or workload redistribution to alleviate user friction [19].

Furthermore, resolving the algorithmic “black-box” dilemma is imperative for real-world deployment. Because algorithmic opacity and privacy concerns severely hinder user trust, future classification frameworks must prioritize Explainable AI (XAI) to provide transparent reasoning alongside robust ethical guardrails [5], [7]. To formalize this adaptive feedback loop, let the estimated cognitive load at time step t be represented as $C_t = f(x_t) \in [0, 1]$. The system triggers a dynamic intervention (e.g., simplifying the generative AI interface or

their practical effectiveness therefore remains an important agenda for future empirical research.

D. Future Research Directions

Addressing RQ3, three critical gaps and corresponding future directives emerge:

Generalizability Across Contexts: Current models lack external validity, primarily relying on controlled laboratories or narrow demographics. Future studies must prioritize cross-cultural validation and expand into diverse, high-friction real-world environments (e.g., gig economy, creative industries) [6], [17], [18].

Real-Time Multimodal Adaptation: Although multimodal fusion excels in offline classification [18], [19], an execution gap remains. Research must transition from static detection toward engineering real-time adaptive systems that trigger dynamic, load-aware interventions based on immediate cognitive friction.

Explainability and Ethical Deployment: Reliance on “black-box” models creates trust barriers, while ethical complexities regarding consent, privacy, and continuous data security re-main underexplored. Future frameworks must integrate Ex-plainable AI (XAI) with robust privacy-by-design principles to ensure transparent, ethical deployment at scale [5].

VI. CONCLUSION

This systematic review synthesizes the intersection of human behavioral modalities and supervised machine learning for classifying technostress in generative AI environments. Findings indicate a clear shift from subjective self-reporting toward multimodal behavioral tracking, including keystrokes, mouse movements, gaze dynamics, and prompt linguistics, to capture behavioral proxies associated with cognitive friction. While traditional classifiers such as Support Vector Machines and Random Forests remain widely used baselines, ensemble architectures, deep learning models, and fuzzy-logic hybrid systems are increasingly explored to improve classification performance. To bridge the gap between offline classification models and adaptive systems, we proposed a human-centered conceptual framework that integrates continuous behavioral sensing, multimodal model inference, explainable decision support, and potential interface adaptation. The framework is conceptual and has not yet been empirically validated. Its future development therefore depends on addressing cross-contextual generalizability, real-time adaptability, subject-independent validation, and ethical transparency. Future research should prioritize explainability, data minimization, and privacy-by-design to support trustworthy computational approaches for human-centered AI interaction.

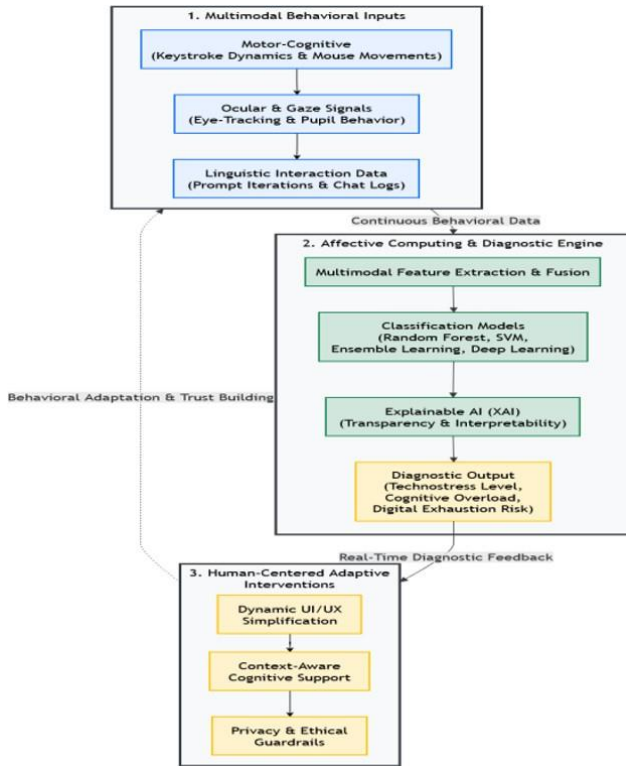


Figure 4. Proposed Human-Centered Framework for Technostress Classification.

introducing a brief pause) if the cumulative stress index exceeds an adaptive threshold $\theta(t)$:

:

$$I_t = \mathbb{I}\left(\sum_{\tau=t-W}^t w_\tau C_\tau > \theta(t)\right) \quad (4)$$

where W is the sliding temporal window, w_τ is a decay weight modeling stress accumulation, and $\mathbb{I}(\cdot)$ is the indicator function. To structure future research directions and operationalize these recommendations, we propose a human-centered conceptual framework (Figure 4). It is important to emphasize that this framework functions as a conceptual framework rather than a validated computational classification system. The feedback loops, intervention thresholds, and adaptive mechanisms depicted in the framework have not yet undergone empirical validation, and

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