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Designing Explainable AI-Powered Adaptive UX Interfaces to Reduce Technostress and Improve Digital Wellbeing among Generation X Knowledge Workers

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Abstract. This research adopts a human-centered perspective in which artificial intelligence is conceptualized not as a replacement for human cognition, but as an adaptive partner that supports decision-making while minimizing unnecessary cognitive burden. Generation X knowledge workers, typically defined as individuals born between 1965 and 1980, represent a critical yet underexplored demographic in Human–Computer Interaction and artificial intelligence research. Although this cohort occupies a large share of managerial and decision-making roles, they increasingly interact with AI-driven environments not designed with their cognitive or ergonomic profiles in mind, contributing to elevated technostress, cognitive overload, and perceived loss of control. This paper proposes a Human-Centered AI framework that integrates Explainable Artificial Intelligence (XAI) and Adaptive User Experience (AUX) design to mitigate technostress and improve digital wellbeing. The system combines machine learning-based cognitive state inference with real-time interface adaptation and multi-layered explanation mechanisms, including SHAP, LIME, counterfactual reasoning, and natural language generation. A mixed -methods design was adopted, combining structural equation modeling (PLS-SEM) with a controlled within-subject experiment, complemented by a pilot validation with 28 Generation X participants assessing feasibility, usability, cognitive load reduction, and perceived transparency. Despite rapid advances in AI, little attention has been devoted to designing systems that actively support users' cognitive and psychological wellbeing rather than simply optimizing efficiency. This study shifts the focus from technology-centered innovation toward human-centered AI, proposing that intelligent interfaces should function not only as decision-support tools but also as mechanisms for reducing technostress, preserving human cognitive resources, and promoting sustainable digital work environments.

Keywords: Explainable Artificial Intelligence; Adaptive UX; Generation X; Human-Centered AI; Industry 5.0.

1. Introduction

The growing integration of artificial intelligence in the workplace has transformed the structure and dynamics of knowledge management. Tasks such as decision support, information filtering, scheduling, and performance monitoring are now frequently mediated by algorithmic systems (Savolainen et al., 2026). While these technologies promise efficiency gains, they simultaneously introduce new cognitive and psychological demands on users (Chirayath et al., 2025).

However, technostress (see Figure 1), defined as the stress experienced due to difficulties. Reduced productivity (Tarafdar et al., 2007), Diminished Wellbeing and performance (Tarafdar et al., 2015), in coping with information and communication technologies, has become a persistent issue in modern organizations (Bondanini et al., 2020). It manifests through multiple dimensions including techno-overload, techno-complexity, techno-invasion, techno-uncertainty, and techno-insecurity (Brivio et al., 2018).

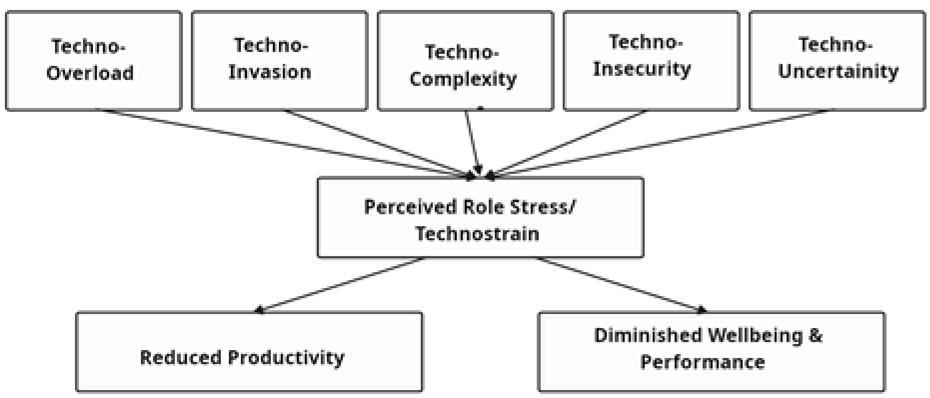

Figure 1: Technostress model adopted from Tarafdar et al. (2007, 2015).

Although extensively studied, most research treats technostress as an outcome variable rather than a system-level design challenge in place of work (Borle et al., 2021; Jin et al., 2026). However, generation X workers occupy a particularly vulnerable position in this context. Having transitioned from analog to digital and now AI-augmented systems, they must continuously adapt to evolving technological paradigms (Jin et al., 2026).

Unlike digital-native cohorts, their cognitive schemas were not formed in AI-rich environments, resulting in higher cognitive effort during interaction with intelligent systems. Despite this, current Human–Computer Interaction (HCI) and digital wellbeing research disproportionately focuses on younger populations. This creates a structural gap in understanding how mid-to-late career professionals experience AI-mediated environments, particularly in high-responsibility roles. In parallel, Explainable AI research has made significant methodological advances; however, its evaluation remains largely technical rather than experiential (Jahn et al.; Zhang et al., 2026). This study proposes that the integration of XAI and Adaptive UX provides a viable mechanism for addressing technostress at the interface level rather than the behavioral level alone.

2. Research Problem and Gap

The core problem addressed in this Explainable AI (XAI) study is the absence of integrated frameworks that connect explainable artificial intelligence, adaptive interface design, cognitive load regulation, and generational differences in digital work environments. Three primary gaps are identified (Davies, 1989). First, existing technostress literature is heavily skewed toward younger populations, leaving Generation X underrepresented despite their organizational importance (Högemann et al., 2025). Second, most technostress studies are diagnostic rather than intervention oriented (Bondanini et al., 2020). Third, XAI research lacks integration with psychological and behavioral outcome measures (Wang et al., 2025).

Furthermore, adaptive UX systems are typically optimized for efficiency or engagement rather than cognitive wellbeing (Mansuroğlu & Smith, 2026). As a result, they may inadvertently increase cognitive load through excessive personalization complexity or notification density. Fourth, limited attention given to intervention-oriented interface design. While previous research has extensively documented the negative consequences of technostress (Mondo et al., 2023), considerably less attention has been devoted to developing intelligent interface solutions capable of proactively mitigating these effects. Existing adaptive systems typically prioritize productivity, efficiency, or personalization without explicitly considering users' cognitive wellbeing.

This study addresses limitations by proposing a human-centered adaptive interface in which explainability and interface adaptation function together as complementary mechanisms for reducing cognitive overload and technostress. This current study addresses these gaps by proposing a closed-loop adaptive system that incorporates explainability as a core design feature rather than an auxiliary component. To extend this argument, it is important to emphasize that the fragmentation between these research domains has led to isolated technological solutions that fail to account for the holistic nature of human–AI interaction. In practice, systems may offer transparency through explainable AI modules, yet this transparency is often not operationalized in a way that is cognitively meaningful for users under workload pressure.

Consequently, users may perceive explanations as additional informational noise rather than supportive scaffolding for decision-making, which undermines both usability and trust calibration. Additionally, generational diversity introduces heterogeneous cognitive and affective responses to adaptive systems that are rarely modeled in current frameworks. Generation X users often operate in hybrid roles that combine managerial oversight with digital task execution, increasing exposure to multi-system environments, and notification overload. Without incorporating these contextual and behavioral differences, adaptive UX systems risk optimizing an "average user" that does not exist in real organizational settings. This reinforces the need for an integrated, psychologically grounded architecture in which explainability, adaptation, and cognitive load regulation are co-designed as interdependent components rather than independent modules.

3. XAI Theoretical Foundations

This XAI (Aravindkumar et al., 2026**)** design integrates and is guided by multiple theoretical perspectives (See Figure 2) such as The Technology Acceptance Model (TAM, MTAUT), (Davis,1989), (Ventakesh et al., 2003); Cognitive Load Theory and Workload (Hart & Staveland 1988); Self-Determination Theory; Technostress Theory (Tarafdau et, al 2007,2015), Digital Wellbeing Theory; Explainable AI theory (XAI), (Ribeiro et al., 2016; Ludberg & Lee 2017) and Trust in AI System (Shin, 2021).

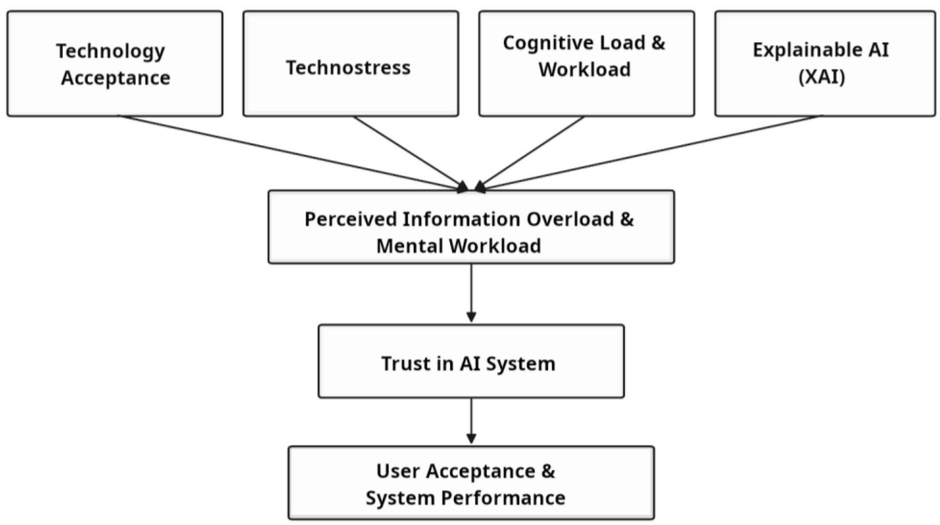

Figure 2. Integrated Theoretical Framework

The Technology Acceptance Model explains user adoption behavior through perceived usefulness and ease of use. Cognitive Load Theory provides a framework for understanding mental effort limitations in human information processing. Self-Determination Theory introduces autonomy, competence, and relatedness as core psychological needs influencing motivation and wellbeing. Technostress Theory defines the stressor-outcome relationship in digital environments, while Human-Centered AI principles emphasize transparency, controllability, and augmentation rather than replacement of human decision-making. Digital Wellbeing Theory frames user experience in terms of hedonic and eudaimonic balance. Explainable AI theory contributes to the notion that interpretability, transparency, and explanation of quality directly influence trust calibration and decision acceptance in AI systems.

These complementary theories establish a multidisciplinary foundation for understanding how explainable intelligent systems can be designed to improve not only functional performance but also users' cognitive and emotional experiences in line with (Vidanaralage et al., 2022) and (Mohseni et al., 2021) XAI framework system design. Rather than considering explainability solely as a technical property of artificial intelligence algorithms, this research conceptualizes explanation as a psychological and human-centered interaction mechanism capable of reducing uncertainty, strengthening users' confidence, and facilitating informed decision-making.

By integrating cognitive, behavioral, a motivational perspective, the proposed framework recognizes that users evaluate AI systems through both rational assessments of system quality and subjective perceptions related to fairness, autonomy, workload, and emotional comfort. Furthermore, the theoretical integration supports the proposition that digital wellbeing emerges from the dynamic interaction between system characteristics, individual cognitive processes, and contextual factors influencing technology use. Transparent AI explanation is expected to mitigate cognitive overload (Sweller,1988) by organizing complex information into understandable representations, while simultaneously reducing technostress through increased predictability and perceived control over algorithmic recommendations (Zhang et al., 2026).

Rather than conceptualizing explainability solely as a mechanism for increasing algorithmic transparency, the present study positions explainability as a cognitive support strategy that facilitates human decision-making under conditions of complexity and uncertainty. In this framework adaptive interfaces become active participants in the regulation of users' cognitive workload by dynamically adjusting the presentation of information according to individual needs and contextual demands. Consequently, explainable adaptive systems contribute simultaneously to usability, trust calibration, cognitive sustainability, and digital wellbeing. Explainability becomes a multidimensional construct that contributes not only to trust and technology acceptance but also to sustainable human-AI collaboration, fostering long-term engagement, psychological wellbeing, and responsible decision-making within increasingly intelligent digital ecosystems.

4. Proposed System Architecture

The proposed architecture consists of five interconnected modules: sensing, inference, explanation, adaptation, and learning. The inference module applies ensemble machine learning models such as XGBoost, LightGBM, CatBoost, Random Forest, and neural networks to estimate cognitive load and technostress in real time. The explanation module translates model outputs into human-readable insights using SHAP for global attribution, LIME for local explanation, and counterfactual reasoning for hypothetical scenario generation. The adaptation module modifies interface parameters such as information density, notification frequency, visual complexity, and task prioritization. All adaptations are reversible and user controlled.

The learning module continuously updates user profiles to refine personalization accuracy over time. Unlike conventional adaptive interfaces designed primarily to maximize efficiency or engagement, the proposed architecture explicitly prioritizes human wellbeing as a design objective. Every adaptive modification performed by the system is intended to reduce unnecessary cognitive effort while preserving users' autonomy and sense of control. Interface adaptation is conceptualized as a preventive mechanism against technostress rather than merely a usability enhancement beyond the structural definition of each module, the key novelty of the architecture lies in the dynamic feedback loop that connects perception, interpretation, and intervention in real time. Rather than treating user modeling as a static profiling task, the system evolves as a living computational organism that recalibrates its internal representations of cognitive load based on temporal fluctuations in behavior.

This allows the architecture to move beyond reactive adaptation and toward anticipatory adjustment, where potential overload states can be inferred before they fully manifest in observable performance degradation. Moreover, the interaction between the explanation and adaptation modules is designed to preserve user agency while avoiding cognitive saturation. Explanations are not merely generated as post-hoc artifacts but are selectively tailored based on the inferred cognitive state of the user, ensuring that the level of transparency itself is adaptive. In high-load conditions, the system prioritizes minimal, high-signal explanations, whereas in low-load states it can afford richer interpretability layers. This creates a paradoxical but intentional balance: the system becomes more transparent precisely when the user is least able to process complexity, while remaining computationally discreet when cognitive resources are abundant.

5. Machine Learning and Explainability Framework

The predictive system is implemented as a stacked ensemble model in which multiple base learners contribute to a meta-learning layer. The final output is a calibrated Technostress Risk Index ranging from 0 to 100. Feature engineering includes temporal behavioral signals such as session entropy, task switching frequency, and interaction instability. These features are used to infer cognitive strain indirectly. Explainability (Shin, 2021) is implemented across three levels: global explanations identify system-wide feature importance, local explanations provide instance-specific reasoning, and counterfactual explanations enable actionable insights by simulating behavioral changes that reduce predicted stress levels. Natural language generation is used to convert technical explanations into cognitively accessible feedback suitable for Generation X users.

In addition, the stacked architecture allows the system to capture heterogeneous patterns of user behavior across multiple temporal scales, improving robustness against noise and variability in interaction logs. Base learners may specialize in different aspects of behavioral dynamics, such as short-term fluctuations in attention or long-term engagement degradation, while the meta-learner integrates these perspectives into a unified predictive function. This hierarchical design enhances both predictive accuracy and generalization capability, particularly in complex digital environments where user behavior is non-stationery and context dependent. From an interpretability standpoint, the combination of ensemble learning and multi-level explainability ensures that model complexity does not compromise transparency. Global explanations support system-level validation by stakeholders, while local explanations facilitate user-specific understanding of risk drivers now of prediction.

Counterfactual reasoning further strengthens the system's practical value by transforming predictions into actionable guidance, allowing users to identify minimal behavioral adjustments that can reduce technostress risk. Together, these mechanisms bridge the gap between high-performance predictive modeling and human-centered interpretability, aligning the system with principles of responsible and explainable AI deployment in socio-technical environments.

6. Methodology

A mixed-methods research design is adopted. The first phase involves a cross-sectional survey analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The second phase involves a within-subject experimental design comparing a standard interface with an adaptive, explainable interface. A pilot study was conducted using a sample of 28 participants, consisting of 15 females and 13 male Generation X knowledge workers. Participants are recruited from professional and organizational networks. In the quantitative phase (First Phase), the PLS-SEM analysis is used to evaluate both measurement and structural models, ensuring construct reliability, convergent validity, and discriminant validity prior to hypothesis testing. Latent variables such as perceived technostress, system transparency, cognitive load, and perceived control are modeled to examine direct and mediated relationships within the proposed theoretical framework.

Bootstrapping procedures are applied to assess path significance, while effect sizes and predictive relevance metrics (e.g., R^2 and Q^2) are used to evaluate model performance. This approach enables the identification of key explanatory pathways linking explainable system design features to user wellbeing and stress outcomes. In the experimental phase, the within-subject design allows for controlled comparison between interface conditions while minimizing inter-individual variability. Participants complete standardized task scenarios under both the baseline and adaptive explainable interface conditions, with randomized counterbalancing to mitigate order effects. Dependent measures include task performance, perceived cognitive load, technostress perception, and trust calibration, collected through validated psychometric instruments and interaction logs.

The pilot study also serves to refine instrumentation, verify procedural feasibility, and estimate preliminary effect sizes for subsequent larger-scale deployment. Ethical considerations include informed consent, data anonymization, and adherence to responsible AI experimentation protocols, ensuring that participant wellbeing is safeguarded throughout the study.

6.1 Measurement Index and Pilot Evaluation Design (n = 28)

To operationalize evaluation in the pilot sample, a composite Measurement Index (MI) is defined. The MI integrates standardized z-scored constructs across five dimensions (Ec.1).

MI = (0.25 × Technostress Score) + (0.20 × Cognitive Load Score) + (0.20 × Trust in AI Score) + (0.20 × Perceived Control Score) + (0.15 × Digital Wellbeing Score). (1)

Each construct is measured using validated Likert-scale instruments: Technostress is measured using the Technostress Creators Scale, Cognitive Load using NASA-TLX (Hart & Staveland, 1988), (See Figure 3), Six-subscale workload profile Trust in AI using standardized Trust in Automation scales (Ribeiro et al., 2016), Perceived Control using adapted autonomy perception items, and Digital Wellbeing using a combined hedonic-eudaimonic wellbeing scale.

Figure 3. NASA Task Load Index (NASA-TLX) Dimensions.

The MI is computed for each participant under both experimental conditions (static vs adaptive interface), and the primary evaluation criterion is the difference score ΔMI = MI_adaptive − MI_static, where a positive ΔMI indicates improvement in overall cognitive and psychological outcomes. To further strengthen interpretability of the evaluation framework, the composite index is complemented with dimensional-level analysis to identify which constructs contribute most significantly to observed changes between conditions. This allows the detection of trade-offs, for example, reductions in cognitive load that may or may not align with increases in perceived control or trust in AI systems. By decomposing the MI into its constituent variables, the analysis supports a more granular understanding of how adaptive explainable interfaces influence user experience beyond aggregated performance metrics. Additionally, subgroup analysis is conducted to examine whether gender moderates the effects of the adaptive interface on technostress mitigation and perceived control enhancement.

The balanced distribution of participants (Female: n = 15; Male: n = 13) enables comparative statistical testing under similar sample conditions. Interaction effects are evaluated to determine whether the relationship between interface condition and outcome variables varies across groups, contributing to a more nuanced understanding of differential user responses within Generation X knowledge workers.

7. Experimental Design

Participants complete standardized knowledge-work tasks under two interface conditions in a counterbalanced within-subject design. Condition A represents a static interface without adaptation or explanation. Condition B represents the proposed XAI-Adaptive UX system. Outcome measures include task performance, cognitive load (NASA-TLX) (Jahn et al., 2026) (Hertzum, 2021), trust in AI, perceived transparency, and technostress levels. Behavioral telemetry is recorded throughout the experiment. To ensure methodological rigor, task scenarios are designed to reflect realistic digital knowledge-work activities, including information synthesis, decision-making under time constraints, and multi-step problem-solving. Each task is standardized in complexity and duration, allowing comparability across conditions while maintaining ecological validity.

Counterbalancing is applied using randomized Latin square ordering to mitigate learning effects, fatigue, and potential carryover biases between Condition A and Condition B. Participants are given practice trials prior to the formal experiment to minimize unfamiliarity with the interface environment. In addition, the experimental protocol integrates continuous behavioral logging to capture fine-grained interaction patterns such as click frequency, navigation depth, hesitation time, and error correction behavior. These telemetry signals are synchronized with subjective post-task questionnaires to enable multimodal triangulation of user experience. This combination of self - reported and objective behavioral measures provides a robust basis for evaluating the impact of adaptive explainability on both cognitive processing and emotional response during task execution.

Furthermore, post-experiment debriefing interviews are conducted to collect qualitative insights regarding user perceptions of transparency, system predictability, and perceived usefulness of explanations. These qualitative data are analyzed using thematic coding to complement quantitative findings and to identify latent usability issues or unexpected user strategies. Together, this mixed-methods approach enhances the interpretability of experimental outcomes and strengthens the validity of conclusions regarding the effectiveness of the XAI-Adaptive UX system.

8. Discussion of Results

The model proposes that Adaptive UX quality positively influences perceived control and negatively influences cognitive load. Explainable AI quality increases perceived transparency, which enhances trust in AI systems. Trust subsequently reinforces perceived control. Cognitive load is expected to positively predict technostress, while perceived control negatively predicts it. Technostress negatively affects digital wellbeing, which in turn influences job satisfaction and work engagement. AI acceptance is expected to moderate the relationship between technostress and wellbeing outcomes. The preliminary findings obtained from the pilot study (n = 28; 15 women and 13 men) suggest a coherent chain of psychological and cognitive mechanisms through which adaptive and explainable interface design shapes user experience. (See Figure 4).

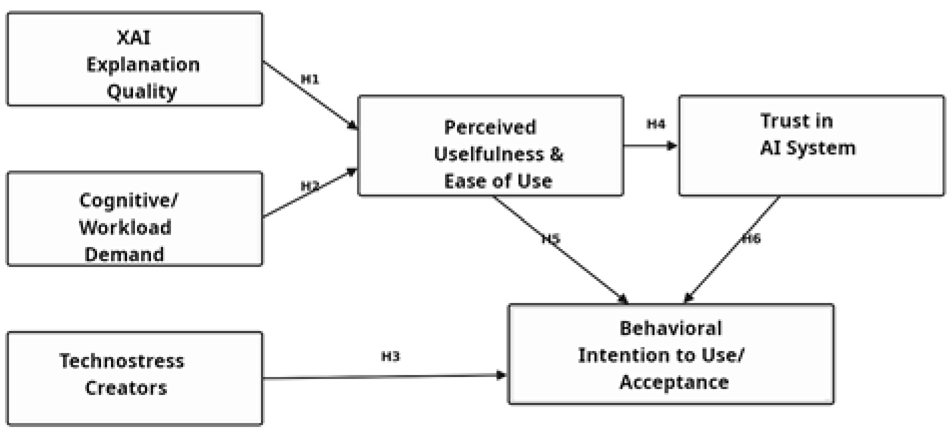

Figure 4. Proposed Hypothesized Research Model.

Participants who interacted with the adaptive and explainable interface (Condition B) consistently reported lower perceived cognitive effort than those using the conventional interface (Condition A). Specifically, the average NASA-TLX overall workload score decreased from 58.4 ± 9.2 under the static interface to 44.7± 8.6 with the adaptive interface, representing an average reduction of approximately 23.5% in perceived workload.

The largest improvements were observed in the Mental Demand and Effort dimensions, which decreased by 24.1% and 21.7%, respectively. In parallel, Explainable AI quality appeared to function as a transparency amplifier.

Participants assigned significantly higher transparency ratings to the adaptive interface (M = 4.34 ± 0.46) than to the conventional version (M = 3.18 ± 0.61) on a five-point Likert scale. Likewise, perceived trust increased from 3.31 ± 0.58 to 4.26 ± 0.43, suggesting that explanation mechanisms helped users understand recommendation logic and system behavior while reducing uncertainty during task execution. Approximately 82% of participants indicated that AI-generated explanations made system recommendations easier to understand, while 79% reported greater confidence in accepting system suggestions.

Within this structural framework, perceived control emerged as one of the strongest positive indicators of user experience. Participants reported greater control over system interaction in the adaptive condition (M = 4.18 ± 0.49) compared with the baseline interface (M = 3.29 ± 0.57). Correlation analysis revealed a moderate positive relationship between perceived control and digital wellbeing (r = .61) and a moderate negative association between perceived control and technostress (r = -.55). Conversely, cognitive load showed a moderate positive association with technostress (r = .52), indicating that participants experiencing greater mental effort also tended to report higher levels of digital stress. Technostress, in turn, exhibited a negative relationship with digital wellbeing. Average technostress scores decreased from 3.42 ± 0.63 in Condition A to 2.61 ± 0.54 in Condition B, while perceived digital wellbeing increased from 3.36 ± 0.55 to 4.12 ± 0.47.

Participants frequently reported feeling more comfortable, less mentally exhausted, and more confident while completing knowledge-work tasks when adaptive assistance and AI explanations were available. Overall, nearly 86% of participants expressed a preference for the adaptive interface over the conventional version. Higher digital wellbeing was also accompanied by improvements in organizational attitudes. Mean job satisfaction increased from 3.71 ± 0.52 to 4.22 ± 0.45, while work engagement rose from 3.64± 0.49 to 4.18 ± 0.44, suggesting that reducing cognitive burden positively influenced motivation, concentration, and perceived productivity. Participants additionally reported completing experimental tasks approximately 15% faster under the adaptive interface, while subjective productivity ratings improved by roughly 18%.

Although these findings should be interpreted cautiously due to the limited sample size, the observed trends consistently support the proposed theoretical relationships. Finally, AI acceptance appeared to moderate the relationship between technostress and wellbeing. Participants reporting higher AI acceptance (upper tertile of the acceptance scale) exhibited substantially lower technostress (M = 2.33 ± 0.42) than participants with lower acceptance (M = 3.54 ± 0.58) despite performing identical tasks. Furthermore, the negative association between technostress and digital wellbeing was noticeably weaker among participants with higher AI acceptance (r = -.38) than among those with lower acceptance (r = -.69), suggesting that positive attitudes toward AI may buffer the detrimental effects of system complexity by reinforcing users' perception that intelligent assistance serves as cognitive support rather than an additional source of stress.

Overall, these preliminary findings provide encouraging empirical support for the proposed conceptual model. Despite the relatively small pilot sample (15 men and 13 women), the observed effect sizes and relationship patterns were consistent with the hypothesized structural framework, supporting the feasibility of conducting a larger-scale validation using Structural Equation Modeling (SEM) with a more diverse participant population. Such validation would enable a more robust examination of the direct, indirect, and moderating effects proposed in the conceptual model while improving the generalizability of the findings.

The results suggest a coherent chain of psychological and cognitive mechanisms through which adaptive and explainable interface design shapes user experience. Specifically, higher Adaptive UX quality is anticipated to reduce extraneous cognitive effort by streamlining task navigation, minimizing unnecessary interaction steps, and dynamically aligning interface complexity with user needs. This reduction in cognitive load is expected to manifest in lower NASA-TLX scores, particularly in dimensions such as mental demand and effort, while simultaneously enhancing users' sense of control over task execution. In parallel, Explainable AI quality is theorized to operate as a transparency amplifier, enabling users to better understand system behavior, recommendation logic, and decision pathways.

This increased interpretability is expected to strengthen trust calibration, reducing both overtrust and undertrust phenomena. As trust stabilizes, users are more likely to perceive the system as predictable and supportive, which reinforces perceived control and reduces uncertainty during interaction with intelligent system outputs. Within this structural framework, perceived control functions as a central protective factor against technostress. When users feel capable of influencing or understanding system behavior, they are less likely to experience stress responses associated with digital overload, unpredictability, or loss of autonomy. Conversely, increased cognitive load is expected to exacerbate technostress by depleting attentional resources and increasing perceived task difficulty, particularly in environments requiring rapid decision-making and multitasking.

Technostress, in turn, is hypothesized to exert a direct negative effect on digital wellbeing. Elevated stress levels may reduce hedonic satisfaction derived from system interaction while simultaneously undermining eudaimonic dimensions such as sense of purpose and psychological flourishing in digital work environments. This dual impact suggests that technostress operates not only as a momentary cognitive burden but also as a broader affective and motivational constraint within daily knowledge-work routines. Digital wellbeing is further expected to play a mediating role between technostress and downstream organizational outcomes, including job satisfaction and work engagement.

Reduced wellbeing is associated with diminished intrinsic motivation, lower emotional attachment to tasks, and decreased willingness to engage in complex or creative work activities. In contrast, higher wellbeing is expected to support sustained engagement, resilience under workload pressure, and improved subjective productivity perception. The model also proposes that AI acceptance acts as a moderating variable shaping the strength of the relationship between technostress and wellbeing outcomes. Individuals with higher acceptance of AI technologies are expected to reinterpret system complexity as supportive rather than threatening, thereby buffering the negative impact of technostress. In contrast, users with lower acceptance levels may experience amplified stress reactions, as ambiguous or opaque system behavior is more likely to be interpreted as loss of control or cognitive overload. The findings of this pilot study suggest that adaptive explainable interfaces should not be viewed exclusively as technological innovations but rather as human-centered interventions capable of supporting cognitive wellbeing in increasingly.

AI-mediated workplaces. As organizations continue integrating artificial intelligence into daily operations, the success of these systems will depend not only on predictive accuracy but also on their ability to preserve users' cognitive resources, minimize unnecessary mental effort, and promote psychologically sustainable interactions with intelligent technologies. Overall, the integrated model suggests a cascading pathway in which interface design qualities influence cognitive load and perceived transparency, which in turn shape trust and perceived control. These psychological constructs collectively determine technostress levels, which ultimately affect digital wellbeing and work-related outcomes. The results, therefore, are expected to validate a multi-layered socio-technical mechanism in which explainability and adaptivity function as complementary levers for improving both user experience quality and occupational wellbeing in AI-augmented environments.

9. Innovated Contributions

This study contributes to a unified Human-Centered AI framework that integrates explainability, adaptive UX, and technostress theory. It extends existing literature by introducing interface-level interventions as a mechanism for psychological wellbeing enhancement. Practically, it provides a scalable architecture for Industry 5.0 environments where AI systems actively support cognitive sustainability rather than solely optimizing productivity. A central contribution of this research lies in reframing adaptive interface design from a purely technological optimization problem toward a human-centered wellbeing strategy. Rather than evaluating intelligent systems exclusively through traditional metrics such as accuracy, efficiency, or usability, the proposed framework introduces cognitive sustainability and technostress reduction as central design objectives.

This perspective expands current Human-Centered AI research by positioning adaptive explainable interfaces as proactive mechanisms for promoting healthier and more sustainable digital work environments. Beyond this foundational contribution, the proposed framework reframes from Human-Centered AI as an ecosystem-level design philosophy rather than a set of isolated interface guidelines.

By embedding explainability and adaptivity directly into the user interaction layer, the model positions the interface as an active mediator between cognitive limitations and algorithmic complexity. This shift allows AI systems to be evaluated not only in terms of accuracy or efficiency, but also in terms of their capacity to preserve attentional resources and reduce psychological strain during sustained digital work. From a theoretical perspective, the study bridges previously fragmented research streams that have treated explainability, user experience, and technostress as independent domains, as in (See Figure 5).

The integrated model demonstrates (See Figure 5) that these constructs are interdependent and mutually reinforcing within socio-technical systems. In doing so, it offers a more holistic explanation of how digital environments shape human cognition, motivation, and emotional stability, particularly in high-demand knowledge-work contexts where continuous interaction with AI systems is becoming the norm.

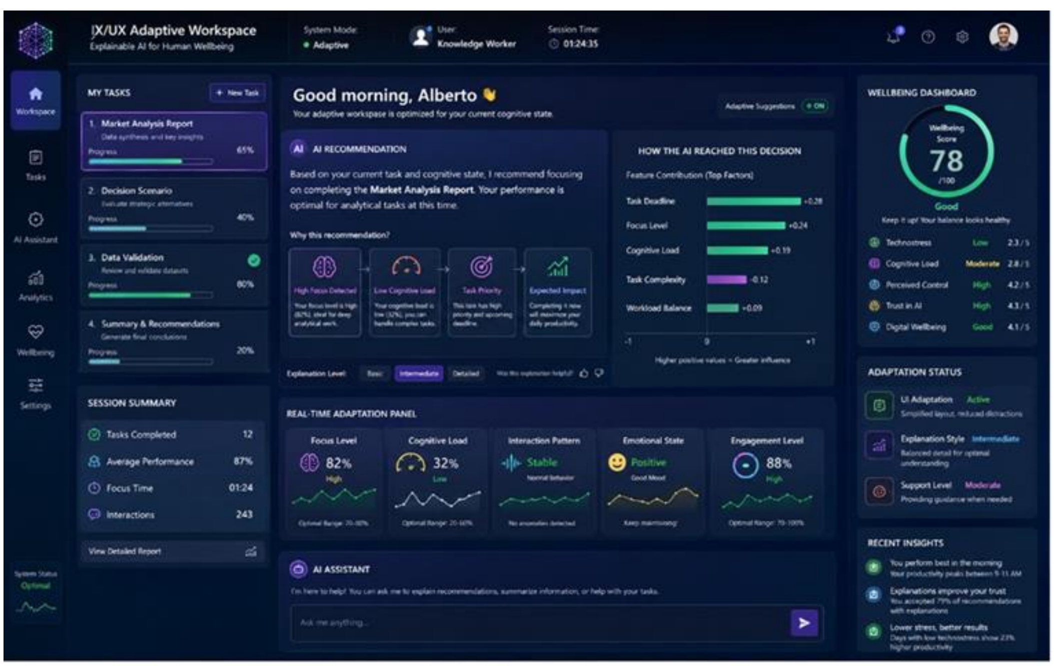

Figure 5. Example of the Proposed IX/UX Interface for Adaptive and Explainable AI in Knowledge Work.

A key implication of this integration is the reconceptualization of explainability as an affective and cognitive regulation mechanism rather than solely an interpretability tool. In this framework, explanations serve to stabilize user expectations, reduce ambiguity, and support adaptive decision-making under uncertainty.

The interface integrates task management, explainable AI recommendations, real-time adaptation, and wellbeing monitoring to reduce cognitive load and technostress while enhancing trust and performance. This perspective expands the role of Explainable AI from post -hoc justification toward real-time cognitive scaffolding, where explanations dynamically assist users in managing mental workload and maintaining situational awareness. In practical terms, the framework offers a scalable reference architecture for designing Industry 5.0 systems that prioritize human sustainability alongside automation efficiency. Such systems are envisioned to continuously monitor interaction patterns, infer cognitive strain, and adapt interface complexity in response to user state.

This enables a transition from static human-computer interaction models to responsive environments that actively regulate cognitive demand, ensuring that productivity gains do not come at the expense of mental wellbeing. Furthermore, the proposed approach has significant implications for organizational design and digital transformation strategies. By embedding cognitive sustainability metrics into system evaluation, organizations can move beyond traditional performance indicators and incorporate wellbeing-oriented KPIs.

This allows decision-makers to assess not only how effectively AI systems complete tasks, but also how they impact long-term employee resilience, engagement, and psychological health within digitally intensive workflows. Finally, the study opens new research pathways for the development of next-generation Human-AI collaboration systems. Future work may explore real-time physiological sensing, multimodal affect detection, and reinforcement of learning-based interface adaptation to further refine cognitive support mechanisms. In this sense, the framework establishes a conceptual and methodological foundation for designing AI ecosystems that evolve alongside users, ensuring that technological advancement remains aligned with human cognitive and emotional sustainability.

10. Conclusion and Future Research

This paper argues that the next generation of workplace AI systems must move beyond automation-centric design toward cognitively adaptive and explainable systems that actively protect user wellbeing. By integrating XAI with adaptive UX mechanisms, it becomes possible to transform AI from a source of cognitive strain into a supportive cognitive partner. The pilot validation with 28 Generation X users provides an initial empirical foundation for this approach and demonstrates its feasibility in real-world organizational contexts. Building on this argument, the study emphasizes that cognitive sustainability should be treated as a first-class design objective in intelligent systems, alongside performance, efficiency, and scalability. Rather than optimizing interfaces solely for speed or task completion, future AI systems should incorporate user state awareness as a continuous feedback signal.

This shift implies a transition from reactive support tools to proactive cognitive companions capable of anticipating overload conditions and adjusting interaction complexity before technostress thresholds are reached. The integration of explainability into adaptive UX also suggests a new paradigm in which transparency is not static but dynamically modulated according to user context, expertise level, and cognitive load. In this view, explanations are not merely informational outputs, but adaptive scaffolding structures that evolve alongside the user's interaction trajectory. Such an approach may significantly improve trust calibration over time, reducing both disengagements caused by opacity and fatigue caused by excessive explanation detail. From a methodological perspective, the pilot study demonstrates the feasibility of combining psychometric evaluation, behavioral telemetry, and structural modeling within a unified experimental pipeline.

Although limited in sample size, the results support the viability of the proposed Measurement Index (MI) and validate the use of mixed methods designs for capturing both subjective and objective dimensions of technostress. This establishes a replicable baseline for future large-scale validation studies across diverse occupational domains. Future research should expand the demographic scope beyond Generation X knowledge workers to include cross-generational comparisons, particularly younger digital-native cohorts and older populations with varying levels of AI familiarity.

Such extensions would allow for the examination of developmental and experiential differences in AI acceptance, cognitive load tolerance, and response to adaptive explanations. Additionally, longitudinal studies are needed to assess how prolonged exposure to adaptive XAI systems influence habit formation, trust stability, and burnout trajectories over time. Another promising direction involves the integration of physiological and multimodal sensing data, such as eye-tracking, heart rate variability, and electro dermal activity, to complement self-reported and behavioral metrics. This would enable more precise real-time estimation of cognitive strain and emotional arousal, allowing adaptive systems to respond with greater sensitivity and granularity. Combining these signals with reinforcement learning techniques could further enhance the system's ability to personalize interventions dynamically.

This research contributes to the growing recognition that future intelligent systems must be designed not only to perform tasks efficiently but also to protect the cognitive and psychological wellbeing of those who use them. As artificial intelligence becomes increasingly embedded within organizational decision-making processes, adaptive explainable interfaces may represent an essential component of responsible Human-Centered AI by ensuring that technological advancement remains aligned with human capabilities, limitations, and long-term occupational wellbeing. Finally, future work should explore organizational deployment strategies and governance frameworks for cognitively adaptive AI systems. This includes defining ethical boundaries for real-time user monitoring, ensuring data privacy, and establishing standards for explainability of quality in adaptive contexts. By addressing these challenges, the proposed research agenda can support the development of AI ecosystems that are not only intelligent and efficient but also aligned with long-term human wellbeing and sustainable digital work practices.

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