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Artificial Intelligence-Driven User-Centered Design and Employee Productivity in AI-Integrated Call Centers: A Systematic Literature Review and Integrative Framework

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Abstract

Introduction: Artificial Intelligence (AI) is rapidly transforming Kenya's Business Process Outsourcing (BPO) sector, exposing call-center agents to technostress from complex systems, algorithmic monitoring and constant connectivity. User-Centered Design (UCD) has been suggested as a means to convert AI from a source of strain to a resource that facilitates work, but no peer-reviewed study has investigated this proposition in Kenya's AI-integrated call centers.

Objective: To synthesize evidence on (i) theories explaining technostress, user centered design and AI adoption; (ii) effect of intuitive interface design on agent productivity; (iii) challenges to AI-user centered design integration in the BPO sector in Kenya; and (iv) directions for future research.

Methods: Searches were performed across ScienceDirect, SpringerLink, PubMed Central, DOAJ and arXiv, according to PRISMA 2020 guidelines and complemented by citation tracking and industry repositories. The final search was completed on 28 September 2026. Of the 54 identified records, 39 sources were eligible and met the quality criteria. Each source was given an evidential weight and synthesized through provisional coding, using the Job Demands-Resources (JD-R) model as the integrating lens.

Results: Adaptive interfaces and formal and structured user involvement received the most empirical support. These reduce cognitive load and increase system use. The obstacles to integration were mostly organizational rather than technical. Only four of the 39 sources referenced Kenya and none were peer-reviewed. The synthesis resulted in an integrative UCD-JD-R framework with seven testable propositions and a prioritized research agenda.

Conclusions: Rapid AI adoption, well-evidenced but geographically distant UCD research and the absence of a Kenya-specific evidence base together form an urgent gap. There is a need for context-specific, longitudinal and organizationally embedded research and the proposed framework provides a foundation for testing how artificial intelligence can be deployed to protect agent well-being and productivity.

Keywords: Artificial intelligence, User-centered design, Technostress, Employee productivity, BPO call centers, Kenya, Adaptive interfaces, Job demands-resources model

Introduction

The use of AI-enabled tools in BPO operations has brought with it a number of advantages such as higher throughput, better quality of service, increased connectivity and real-time customer data [1]. Kenya's BPO organizations are using AI to compete in changing service markets and to find new sources of competitive advantage [2]. When strategically designed and implemented, AI tools can function as job resources that improve both individual agent performance and organizational-level outcomes [3]. However, the use of AI has also

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required employees to continually adapt to changing system requirements and rising performance expectations. Many feel they cannot effectively deal with their interactions with AI-integrated platforms [4].

Artificial intelligence and Information and Communication Technology (ICT) can lead to stress conditions in the workplace, referred to as technostress [5]. Technostress refers to the negative effects of modern technology use, which cause cognitive overload, anxiety and reduced performance [6]. It is often described as a salient "dark side" phenomenon that typifies the detrimental impacts of technology use in occupational context [7]. In AI-augmented call-centers, technostress is particularly high: agents have to deal with real-time AI recommendations, algorithmic performance monitoring, multi-channel dashboards and customer interactions, all of which aggregate in more challenging ways than traditional ICT-intensive roles (Table 1). In the wider literature, UCD has been proposed as a mechanism of reorienting artificial intelligence systems from the technostress-inducing demands to productivity-supporting resources [4,8]. However, the specific application of UCD within the framework of AI-integrated BPOs in Kenya remains unstudied.

Techno-stressor	Description and AI-specific manifestation in call centers
Techno-overload	Agents are overwhelmed by AI task recommendations, real-time performance dashboards and multi-channel communication demands. The use of AI in call centers increases the cognitive load on agents, who have to deal with algorithmic cues, scripts for customer interactions and constant performance monitoring, all of which is more demanding than legacy ICT-intensive work [6,7].
Techno-complexity	Opaque algorithmic outputs and frequently changing AI tools force agents to spend time learning and understanding them. In Kenya's BPO industry, AI is being integrated without adequate training frameworks, making techno-complexity a significant strain that adversely affects agent productivity and service quality [6,9].
Techno-invasion	Constant connectivity extends work beyond designated hours and this is exacerbated by the continuous monitoring of performance through algorithmic management systems, resulting in increased stress and diminished work-life equilibrium [10,11].
Techno-uncertainty	Regular updates to AI systems and evolving algorithms generate ongoing ambiguity regarding the competencies required by agents. The pressure is heightened in Kenya's BPO sector, as the adoption of AI is advancing more swiftly than the availability of structured reskilling programs for agents [6,9].
Techno-insecurity	Automation powered by artificial intelligence jeopardizes the employment stability of agents engaged in repetitive duties, heightening opposition to AI integration and fostering organizational discord. Giwa and Ngepah illustrated *via* econometric analysis that investments in AI are markedly and adversely correlated with low-skilled employment in South Africa, a macroeconomic trend pertinent to Kenya's BPO labor force. The exposure to AI increases the perception of job insecurity, even in the absence of actual job displacement [12,13].
Source: Adapted from Ragu-Nathan et al., with call-center manifestations synthesized from the sources cited in each row [6].	

Table 1: Technostress creators and their manifestation in AI-integrated call centers.

With Kenya's BPO sector growing and digitizing at a rapid pace, it is important to understand how AI-driven technostress may impact employees and organizations. Kenya is one of the leading BPO destinations in Africa, with a young multilingual workforce and a government policy conducive to growth, drawing foreign operators [2,14]. AI-assisted services are already available on the market. For instance, Kenyan BPO service providers provide AI-augmented data processing, content moderation, voice analytics and market research [15]. However, poor design of the AI implementation with emphasis on user experience and system design might lead to technostress, high turnover and loss of productivity among the agents who are the operational backbone of the sector [16]. Although there have been industry reports on AI adoption in the BPO industry in Kenya, peer-reviewed academic research that explores the effect of AI-UCD on technostress and productivity in this context is absent; this review addresses that gap.

This review responds to that gap and goes beyond a narrative summary in three ways. First, it maps and weights the available evidence so that the strength of each conclusion is explicit. Second, it integrates the JD-R model, technostress theory, task-technology fit and technology acceptance into a single framework, from which seven testable propositions are derived. Third, it translates the findings into a prioritized research agenda and into practice guidance for BPO operators and policymakers in Kenya.

The remaining portion of the paper is organized as follows. The rest of this introduction places the review within the framework of previous reviews, states the research questions and defines the main ideas. The review protocol is described in the Methodology section. The Results part presents the evidence profile, the findings for each research question, the strength and transferability of the evidence and the integrative framework. The Discussion provides interpretation of the findings and implications, a research agenda, research trends and limitations.

Previous literature reviews

Several systematic and scoping reviews have examined technostress in organizational contexts. Pansini et al. conducted a PRISMA-guided review positioning technostress within the JD-R model, confirming that ICT is predominantly conceptualized as a job demand and identifying design-level resources as an under-explored intervention [4]. Rohwer et al., mapped 62 studies on preventing and

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coping with work-related technostress and reported a shortage of prevention research [17]. Tarafdar et al., reorganized the technostress literature around a trifecta of techno-eustress, techno-distress and design, arguing that system design decisions determine which outcome predominates [8]. Mdhluli systematically reviewed AI-supported employee assistance programs in South Africa, identifying a gap in context-specific design guidance for African organizational settings [18]. Bahamondes-Rosado et al. reviewed technostress during the COVID-19 lockdown period [19]. Borle et al., found that workers of high socioeconomic position are over-represented in technostress research, suggesting that lower-wage, high-volume occupations such as call-center work are under-studied, while La Torre et al., clarified technostress definitions, symptoms and risk factors [20,21]. From the literature reviewed above, it is evident that technostress has become a well-established and urgent area of scholarly inquiry, particularly as AI accelerates the technological demands placed on workers. However, no existing review has examined the specific convergence of AI, UCD and technostress in call-center or BPO environments and none has examined this intersection within Kenya's BPO sector. The current study addresses this gap through a structured systematic literature review organized around the following four research questions.

I. What theoretical frameworks explain technostress, user-centered design and AI adoption in AI-integrated work environments?
II. What is the influence of intuitive user interface design on employee productivity in AI-integrated call center environments in Kenya's BPO sector?
III. What are the challenges facing the integration of Artificial Intelligence and User-Centered Design in call center environments in Kenya's BPO sector?
IV. What strategic directions should guide future research on AI-driven UCD in Kenya's BPO sector?

Table 2 compares these reviews with the present one. None of them combines AI-specific stressors, UCD as an intervention and the call-center or BPO setting; none examines an East African context; and none derives testable propositions linking interface design to productivity. The present review addresses these gaps.

Review	Type	AI-specific	UCD focus	Call center / BPO	African context	Propositions / framework
La Torre et al. [21]	Systematic review	No	No	No	No	No
Borle et al. [20]	Systematic review	No	No	No	No	No
Rohwer et al. [17]	Scoping review	No	Partly	No	No	No
Pansini et al. [4]	Systematic review	No	Partly	No	No	JD-R positioning
Bahamondes-Rosado et al. [19]	Systematic review	No	No	No	No	No
Mdhluli [18]	Systematic review	Yes	Partly	No	South Africa	No
This review	Systematic review	Yes	Yes	Yes	Kenya	Yes (7 propositions)

"Partly" indicates that design or prevention measures are discussed but are not the organizing focus. Abbreviations: AI, artificial intelligence; UCD, user-centered design; BPO, business process outsourcing; JD-R, job demands-resources.

Table 2: Comparison of related reviews with the present review.

Key concepts

User-Centered Design (UCD) is a design paradigm that incorporates the demands, limitations and preferences of end users during all phases of system development and implementation. In AI-integrated work settings, UCD is about intentionally designing interfaces, processes and feedback loops to lower cognitive load, improve task-technology fit and limit the stress-producing power of complicated artificial intelligence systems on frontline workers. The concept of UCD was introduced in the 1980s as a design philosophy and has become a key theme in research on Human-Computer Interaction (HCI) [22]. This constitutes the basis for the study and construction of usable and readily available technological systems.

Technostress was characterized by Brod as "a modern disease of adaptation caused by an inability to cope with new computer technologies in a healthy manner" [23]. This term has since been expanded by scholars to include the psychological, physiological and behavioral responses that occur as a consequence of the demands of employing digital technology at work. Ragu-Nathan et al., identified five technostress creators: techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty [6]. Collectively, these are the dominant mechanisms by which technology causes occupational stress. In AI-integrated call centers, algorithmic management, real-time performance monitoring and constant system changes amplify these creators, making UCD a crucial organizational tool for mitigating technostress. Weil and Rosen extended the definition of technostress to include any negative influence on attitudes, thoughts, behaviors, or psychology produced by technology, embracing both direct cognitive effects and the indirect social and organizational repercussions of technological change [24].

In a call center, artificial intelligence refers to the application of machine-learning-based systems to perform functions such as natural language processing, call routing, sentiment analysis, agent-assist

tools, predictive analytics and automated quality monitoring. These technologies operate alongside human agents, establishing a hybrid human-AI workflow that poses additional cognitive and adaptive demands on workers. We argue that AI system design, individual agent competence and organizational support structures jointly determine whether AI is a job resource that increases productivity or a job demand that causes technostress [3,8]. This dual character of AI, as either a job resource or a job demand, is the main analytical tension that UCD must manage in the call-center context.

Kenya's BPO sector is among the most rapidly growing outsourcing industries in Africa. Major international call-center operators have been attracted by government investment in digital infrastructure, a young English-speaking workforce and competitive operating costs. The Kenyan BPO industry has begun commercializing AI-enhanced services, incorporating AI-augmented data tagging, voice analytics and digital outsourcing services [14,15]. This review addresses the lack of peer-reviewed, theory-based research on AI-UCD and productivity. Next, the systematic approach to identify, screen and analyze literature relevant to the four research questions is described.

Methodology

Review protocol

The PRISMA 2020 framework improved findings quality, transparency and reliability. A structured method for identifying, screening, assessing and including relevant literature, PRISMA is widely used for systematic reviews [25]. The review included PRISMA 2020-compliant English language studies from 2007 to 2026 and seminal theoretical and empirical works regardless of publication date. Promotional material without verifiable research or data, AI implementation studies without an employee or workplace dimension and non-English sources were excluded. The protocol was adapted in two ways, both transparently reported given the breadth of the topic across peer-reviewed research and a rapidly changing industry. Industry and policy documents were included; to frame the Kenyan context and each source was given an evidential weight so material that only provides context does not have the same weight as empirical evidence (see Quality appraisal and evidential weighting).

Search strategy

Searches were performed on ScienceDirect, SpringerLink, PubMed Central, arXiv and Directory of Open Access Journals (DOAJ) targeting publications from 2007 to 2026. Targeted searches of institutional and industry repositories were used to identify Kenya-specific gray literature. Boolean operators (AND, OR) were used to combine the search terms relevant to each research question. The main search terms were technostress, user-centered design, adaptive interfaces, integrated dashboards, BPO, call centers, Kenya, AI implementation, employee productivity, job demands-resources, algorithmic supervision and organizational challenges. The terms were chosen for their relevance to the four research questions of the review and collectively they cover the theoretical, empirical and contextual aspects of the study. Citation tracking of key foundational works was used to supplement the search to ensure that seminal and recent literature were captured.

Table 3 lists the search-string blocks used for each research question. The final search was completed on 28 September 2026.

RQ	Search-string block (combined with AND / OR)
RQ1	("technostress" OR "techno-stress" OR "job demands-resources" OR "task-technology fit" OR "UTAUT") AND ("artificial intelligence" OR "AI deployment" OR "algorithmic")
RQ2	("user-centered design" OR "user-centred design" OR "adaptive interface" OR "consolidated dashboard" OR "user involvement") AND ("productivity" OR "performance" OR "cognitive load")
RQ3	("algorithmic management" OR "algorithmic supervision" OR "organizational challenges" OR "barriers") AND ("AI" OR "human-centered AI") AND ("workplace" OR "call center" OR "BPO")
RQ4	("BPO" OR "call center" OR "contact center") AND ("Kenya" OR "Africa" OR "developing country") AND ("AI" OR "technostress" OR "employee productivity")
Abbreviations: RQ, research question; UTAUT, Unified Theory of Acceptance and Use of Technology; BPO, business process outsourcing.	

Table 3: Search-string blocks by research question.

Literature search

The search covered a broad range of relevant fields, such as information systems, human-computer interaction, organizational psychology, occupational health, management and BPO studies. After the search, articles and reports that fulfilled the designated inclusion criteria were obtained. A total of 54 records were identified throughout all databases and repositories. These encompassed peer-reviewed journal articles, systematic reviews, conference proceedings, arXiv preprints and industry and market analyses offering contextual insights on Kenya's BPO industry that were absent in scholarly literature. This systematic search yielded a substantial body of relevant material for subsequent screening and analysis.

Screening and selection

Screening and selection were performed as per the PRISMA 2020 flow diagram [25]. The search results were initially screened by inclusion and exclusion criteria. Duplicates and irrelevant records (n = 9) were excluded and 45 records were screened by title and abstract. Six records were excluded as promotional material with no verifiable research or data. We assessed the full text of 39 sources for eligibility criteria (i.e. clear description of methodology, findings grounded in

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data or validated theory and peer-reviewed or credible industry-document status) and all 39 sources met the inclusion criteria. This leaves 39 sources for final review. Table 4 shows the inclusion and exclusion criteria and Table 5 shows the PRISMA screening results.

Criterion	Eligibility	Elimination
Type of sources	Peer-reviewed journal articles, systematic reviews, conference papers, arXiv preprints, credible industry and market reports	Promotional content with no citable research or data
Selection criteria	Sources addressing technostress, UCD, AI-integrated systems, call-center or BPO productivity, published in English	AI adoption studies with no employee or workplace dimension; sources unavailable in English
Language	English-language sources only	Non-English sources
Subject area	Information systems, HCI, occupational psychology, management, BPO and call-center research, Kenya and African context	Studies without relevance to employee wellbeing, UCD, AI adoption, or BPO productivity
Timeline coverage	2007–2026; foundational theoretical works included regardless of date	Sources pre-dating 2007 unless foundational theoretical works

Table 4: Criteria followed in the eligibility and elimination of sources.

Screening stage	Number of sources
Records identified across all databases and repositories	54
Duplicates and off-topic records removed	9
Records screened (title and abstract)	45
Promotional / no research data excluded	6
Full-text sources assessed for eligibility	39
Sources included in final review	39

Table 5: Screening results following the PRISMA 2020 workflow.

Screening followed the PRISMA 2020 statement adapted for a literature-based search process appropriate to this paper's scope [25]. No records were excluded at the full-text stage because ineligible sources had already been removed during title-and-abstract screening. The PRISMA 2020 flowchart is depicted in Figure 1.

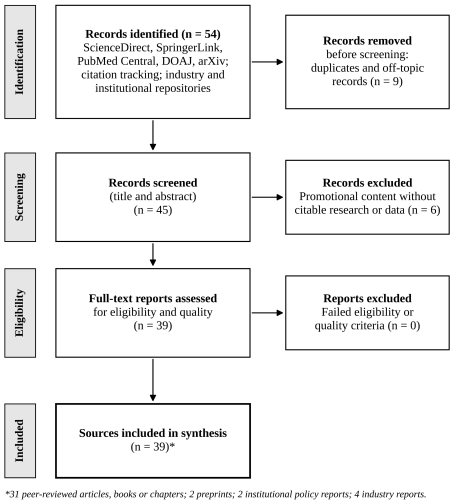


Figure 1: PRISMA 2020 flow diagram of source identification, screening and inclusion.

Quality appraisal and evidential weighting

Each comprehensive article was screened against three quality criteria: (a) a clearly described method or argument; (b) findings grounded in data or in established theory; and (c) peer-reviewed or credible institutional status. Then, to make the strength of each conclusion explicit, every source was allocated one of three evidential weights. High (H): Peer-reviewed empirical studies with validated measures, experimental or longitudinal designs, systematic reviews or meta-analyses. Moderate (M): Peer-reviewed cross-sectional or qualitative studies, conceptual/theoretical work and preprints. Contextual (C): Industry and policy reports, these are used only to describe the Kenyan and institutional setting and not as evidence of causal relationships. Table 6 shows the weights for each source.

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No.	Source	Design; Setting	Theme	Weight	Principal finding
1	Bakker & Demerouti [3]	Theoretical	T1	M	Foundational JD-R model positioning AI as job demand or resource depending on design and organizational support. Core theoretical lens for the entire review.
2	Goodhue & Thompson [26]	Survey; USA	T1, T2	H	Validated TTF as predictor of performance over and above attitudes; justifies argument that UI alignment with task demands is functionally necessary.
3	Edwards [27]	Theoretical review	T1	M	Theoretical review explaining why the same AI system generates different stress outcomes across agents depending on competence and values fit with system design.
4	Lazarus & Folkman [28]	Theoretical (book)	T1	M	Cognitive-appraisal model positions UCD features as coping resources that can be deliberately embedded in AI system design to buffer technostress.
5	Ragu-Nathan et al. [6]	Survey; USA	T1, T2	H	Validated five technostress creators and organizational inhibitors; most cited measurement instrument; structures this review's AI-specific stressor analysis.
6	Venkatesh et al. [29]	Longitudinal field study; USA	T1	H	Adoption-behavior model explaining agent acceptance or rejection of AI tools based on performance expectancy, effort expectancy, social influence and facilitating conditions.
7	Pansini et al. [4]	Systematic review	T1	H	PRISMA systematic review confirming JD-R as valid technostress lens and identifying design-level resources as under-explored intervention area.
8	Scholze & Hecker [30]	Survey; Germany	T1	M	Extended JD-R to digital workplace; empirically validated digital demands and digital resources as distinct constructs with opposing wellbeing effects.
9	Tarafdar et al. [8]	Conceptual review	T1, T3	M	Identified system design as the pivotal causal mechanism determining whether technology generates eustress or distress; directly underpins this review's central argument.
10	Chang et al. [31]	Three-wave survey; China	T1, T2	H	Three-wave time-lagged study; AI challenge *vs*. hindrance stressors have opposing effects on adoption intention; technical self-efficacy moderates both paths.
11	Yam et al. [12]	Multimethod	T3	H	Multimethod evidence that AI exposure generates job insecurity and maladaptive behavior even without actual job displacement; relevant to Kenya's BPO agents.
12	Wang & Wang [32]	Scale development	T1	M	Psychometrically validated AI-specific anxiety instrument covering job replacement fear, unknown AI capabilities and ethical anxiety sub-dimensions.
13	Saleem et al. [33]	Survey; Pakistan	T2, T4	M	Training and creative self-efficacy moderate technostress-performance relationship positively; supports integrated UCD-organizational support intervention approach.
14	Fischer & Riedl [34]	Experiment	T2	H	Controlled experiment showing instrumental support restores task performance faster; validates design-embedded support as high-value productivity intervention.
15	Malik et al. [35]	Survey; Pakistan	T1, T3	M	Dual-path COR model; organizational support moderates technostress-exhaustion path in a resource-constrained developing-country context.
16	Montazer & Ahmadi [36]	Experiment	T2	H	Controlled experiment demonstrating adaptive interface reduces cognitive load, errors and hesitation *vs*. static interface; strongest causal evidence for adaptivity.
17	Carrera-Rivera & Larrinaga [37]	Technical review (preprint)	T2	M	Technical description of ML-based adaptive UI engineering; provides implementation pathway for adaptive interfaces in call-center AI platforms.
18	Hamdani & Chihi [38]	Review and simulation	T2	H	Simulation-validated adaptive HCI model demonstrating efficiency gains, stress reduction and fault-recovery time improvements over static baselines.
19	Wang [39]	Experiment (preprint)	T2	M	18% cognitive load reduction and 22% satisfaction increase with adaptive interface; greatest gains during sustained interactions mirroring call-center work.
20	Bano & Zowghi [40]	Systematic review	T2	H	Systematic review of 87 primary studies; 52 found positive relationship; most authoritative evidence base for user feedback involvement as a UCD dimension.

21	Olson & Ives [41]	Field study	T2	M	Formal, structured feedback mechanisms most effective; warns against treating user involvement as monolithic; early but methodologically careful finding.
22	Baroudi et al. [42]	Survey	T2	M	Behavioral confirmation that involvement predicts actual system use, not merely satisfaction; establishes a direct productivity pathway through UCD involvement.
23	McKeen et al. [43]	Survey	T2	M	Involvement most consequential under high task and system complexity; directly applicable to AI-integrated call-center context as inherently complex.
24	Poisat et al. [9]	Qualitative; South Africa	T3	M	South African HR leaders see AI as essential for competitiveness but stress the need for workforce development, reskilling and careful governance; relevant to Kenya.
25	Mdhluli [18]	Systematic review; South Africa	T4, T3	H	Identifies absence of context-specific AI design guidance for South Africa; confirms that African organizations need localized rather than imported frameworks.
26	Giwa & Ngepah [13]	Econometric; South Africa	T3	M	AI investment negatively associated with low-skilled employment; quantifies socio-economic stakes of AI adoption without adequate UCD safeguards in BPO.
27	Soyangco et al. [1]	Survey; Philippines	T2	M	Tools and technology are significant predictors of BPO agent productivity in a developing-country context; provides external validity for UCD-productivity claim.
28	Callin [14]	Industry report; Kenya	T3	C	Industry report profiling AI-enhanced services in Kenya BPO and highlighting AI voice technology integration challenges. Kenya-specific contextual source.
29	Site Selection Group [2]	Industry report; Africa/Kenya	T3	C	Documents major AI-related BPO investments in Kenya including CCI Global Tatu City; confirms AI adoption in Kenya's BPO sector is at scale.
30	Outsource Accelerator [15]	Industry report; Kenya	T3	C	AI capabilities commercially operational in Kenya BPO; confirms the urgency of AI-UCD research is grounded in current sector reality rather than speculation.
31	HelloDuty [16]	Industry report; Kenya	T3	C	Links shift to digital/hybrid channels to improved agent wellbeing; provides historical and operational Kenya BPO context unavailable in academic literature.
32	Gorichanaz [44]	Qualitative interviews	T3	M	Five organizational barrier patterns; reveals AI-UCD failures are predominantly organizational and political rather than technical; culture and strategy are decisive.
33	Nair et al. [45]	Mixed methods; Sweden	T3	M	Twelve-concept barrier taxonomy; resourcing, leadership and change management are dominant structural challenges applicable across sectors including BPO.
34	Winby & Xu [46]	Conceptual model	T3, T4	M	Five-stage HCAI-MM; cultural resistance and resource constraints are key implementation barriers; provides maturity progression framework for organizations.
35	ILO [11]	Policy report; cross-national	T3	C	Cross-national evidence of work intensification from algorithmic management; specific African risk identified. Institutional authority adds significant credibility.
36	EPRS [47]	Policy report; EU	T3	C	Managers' report accountability ambiguity and algorithmic opacity; governance gaps affect the entire organizational hierarchy, not only frontline call-center agents.
37	Hlatshwayo et al. [48]	Conceptual framework; South Africa	T3, T4	M	TOE framework; algorithmic bias, privacy, transparency as critical African risks; confirms generic high-income-economy AI frameworks are inadequate for Africa.
38	Kellogg et al. [10]	Narrative review	T3	M	Synthesizes algorithmic management evidence; surveillance, work-pace acceleration, reduced autonomy and worker resistance documented consistently across industries.
39	Harunavamwe & Ward [49]	Survey; South Africa	T2, T4	M	Model including technostress, work-family conflict and organizational support explained 47% of the variance in workplace flourishing; organizational support had the strongest direct effect.
Abbreviations: T1–T4, themes (see Table 7); H, high; M, moderate; C, contextual.					

Table 6: Characteristics of the 39 included sources — research papers, design, themes, evidential weight and findings.

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Data analysis

Source type, setting, design, constructs and main findings were extracted. The researcher develops a preliminary start list of codes based on the research questions and theoretical framework prior to analyzing the literature. These codes are refined as the literature is analyzed [50]. Sources were reviewed iteratively to refine the codes. The four research questions T1) Theoretical Frameworks and Concepts, (T2) Intuitive UI Design and productivity outcomes, (T3) Organizational Challenges of AI-UCD Integration and (T4) Strategic Research Directions – led to four theme codes during coding. Table 7 lists the four themes and codes. Table 6 shows coding, design and evidence weight for 39 sources.

Theme	Code	Definition
T1. Theoretical Frameworks and Concepts	JD-R and Technostress Theory	The Job Demands-Resources model positions AI systems as either job demands (technostress sources) or job resources (productivity enablers) depending on design and organizational support. UCD is the design mechanism through which demands are converted into resources [3,4].
	Technology Adoption Frameworks	UTAUT and Task-Technology Fit explain why agents accept or reject AI tools based on performance expectancy, effort expectancy, social influence, facilitating conditions such as training and the fit between tool features and task demands. Adoption failure amplifies technostress by creating techno-complexity and techno-uncertainty [26,29].
	Cognitive Appraisal and P-E Fit	The transactional stress model and P-E Fit theory explain how the same AI system produces different stress outcomes across individual agents depending on competence, coping resources and fit between system design and task requirements [27,28].
T2. Intuitive UI Design and Productivity Outcomes	Adaptive Interface Design	Interfaces that dynamically adjust complexity, layout and contextual prompts to individual agent competence and workload state. Controlled experiments demonstrate measurable reductions in cognitive load, error rates and hesitation, with corresponding performance improvements [36,38,39].
	User Feedback Involvement	Structured mechanisms through which call-center agents provide input into the design and governance of AI systems. A predominantly positive relationship with system acceptance and actual system use is reported across four decades of IS research [40,41,43].
	Cognitive Load and Technostress Reduction	Intuitive design directly reduces cognitive resource demands of operating AI-integrated platforms, buffering techno-overload and techno-complexity, the two most directly productivity-relevant of the five technostress creators, in line with Ragu-Nathan et al. [6].
T3. Organizational Challenges of AI-UCD Integration	Cultural and Structural Barriers	Organizational cultures that prioritize delivery speed over user experience, competing strategic objectives and unclear accountability structures are major non-technical barriers to AI-UCD integration. UCD failures stem mainly from organizational and political rather than technical issues [44,45].
	Algorithmic Surveillance and Autonomy Loss	AI-driven monitoring systems reduce worker autonomy, increase work pace and generate resistance. Algorithmic management constitutes a distinct category of technostress in AI-intensive roles, documented consistently across industries and countries [10,11].
	African Context Constraints	African organizational settings face infrastructure limitations, skills gaps, data-privacy vulnerabilities and an absence of localized AI-UCD frameworks, constraints likely to apply to Kenya's BPO sector. Generic high-income-economy frameworks fail to account for these distinctive constraints [18,48].
T4. Strategic Research Directions	African-Specific Framework Development	Persistent need for AI-UCD frameworks validated in African BPO contexts rather than imported from high-income economies. Kenya-specific empirical evidence is entirely absent from the current peer-reviewed literature [18,31,48].
	Longitudinal Research Designs	Longitudinal and experience-sampling methodologies are essential for assessing UCD interventions over various temporal and deployment stages [31].
	Integrated Organizational-Technical Interventions	Interventions that combine interface design with training, organizational support and governance. Organizational support was the strongest predictor of workplace flourishing amid technostress [33,49].
Abbreviations: JD-R, job demands-resources; UTAUT, Unified Theory of Acceptance and Use of Technology; P-E, person-environment; UI, user interface; UCD, user-centered design; BPO, business process outsourcing.		

Table 7: Provisional coding framework — themes, codes and definitions for AI-driven UCD derived from the literature.

Results

The analysis draws on the provisional coding scheme presented in Table 7 and the 39 sources summarized in Table 6.

Profile of the evidence base

Table 8 profiles the 39 included sources. The evidence base is recent: just over half of the sources (20 of 39) were published between 2024 and 2026, reflecting the rapid growth of research on AI at work.

The largest group is quantitative surveys and econometric studies (14 sources), followed by theoretical and conceptual works (7). Experimental and simulation studies, the designs best suited to causal claims about interface design, number only four. Nine sources concern African settings, but only four concern Kenya and all four are industry reports. The most important feature of the evidence base is therefore that the peer-reviewed knowledge on which Kenyan operators might draw comes from other countries and other sectors.

Type of evidence	Before 2007	2007–2019	2020–2023	2024–2026	Total (%)
Theoretical / conceptual	1	3	1	2	7 (17.9)
Systematic or narrative review	0	1	2	1	4 (10.3)
Experiment or simulation	0	0	1	3	4 (10.3)
Quantitative survey / econometric	5	1	3	5	14 (35.9)
Qualitative or mixed methods	0	0	1	3	4 (10.3)
Institutional policy report	0	0	0	2	2 (5.1)
Industry report	0	0	0	4	4 (10.3)
Total	6	5	8	20	39 (100)
African-context sources: 9 (South Africa 5; Kenya-focused 4, all industry reports). Classification follows Table 6.					

Table 8: Profile of the 39 included sources by type of evidence and publication period.

Theoretical frameworks explaining technostress, UCD and AI adoption

The Job Demands-Resources (JD-R) model is the most frequently used framework [3]. A recent systematic review affirms that ICT and AI systems are mostly viewed as job demands that induce psychological stress [4]. This positions UCD as a design approach that may transform AI tools from job demands into job resources that enhance engagement and mitigate technostress. Scholze and Hecker expanded the traditional JD-R framework to encompass workplace digitization by delineating digital job demands and digital job resources as separate entities, discovering empirical evidence for the adverse relationship between digital demands and wellbeing, as well as the beneficial correlation between digital resources and engagement [30].

The Task-Technology Fit (TTF) theory and the Person-Environment (P-E) Fit theory are complementary, addressing performance and strain respectively [26,27]. TTF argues that the extent to which task demands and technology features match is a better predictor of performance than attitudes toward technology, which supports the notion that AI interfaces must fit the task, not merely be well designed in the abstract. The P-E Fit hypothesis helps to explain how the same AI system can cause different stress outcomes for different agents depending on their skills, needs and values. The transactional model of stress and coping defines technostress as a dynamic interaction, in which primary appraisal (is this AI system a threat?) and secondary appraisal (do I have the resources to cope?) influence technostress [28]. UCD features can act as coping resources that are deliberately integrated into system design.

The study of AI related stressors in the BPO environment in Kenya is based on the five-creator typology of Ragu-Nathan et al., the most widely used measurement instrument in technostress research [6]. In their review Tarafdar et al., restructured the literature around the technostress trifecta (techno-eustress, techno-distress and design) and argued that system design decisions are the critical causal factor that determines which outcome prevails and this is the underlying rationale for this review [8]. The Unified Theory of Acceptance and Use of Technology (UTAUT) offers an adoption-behavior dimension that explains agents' intention to adopt AI tools in terms of performance expectancy, effort expectancy, social influence and facilitating conditions [29]. The major theoretical limitation identified in all the reviewed theories is the lack of a unified model that integrates JD-R, TTF, technostress creators and UTAUT for AI-enabled call-center environments in the African context.

Influence of intuitive user interface design on employee productivity

Of the four thematic areas, the relationship between intuitive UI design and employee productivity in AI integrated work environments is the most empirically developed. Montazer and Ahmadi compared the performance of adaptive versus static interfaces in a metaverse environment in a controlled experiment using the NASA Task Load Index [36]. They found that the adaptive interface that dynamically changed the complexity of the layout produced significantly lower cognitive load, fewer errors and less hesitation under complex, time-constrained task conditions that were in some respects comparable to call-center workflows. Wang designed a fatigue-aware adaptive interface using multimodal deep learning and reinforcement learning and reported an 18 percent reduction in cognitive load and a 22 percent increase in user satisfaction compared to static interfaces, with the biggest improvement happening during sustained interactions, a situation similar to call-center work, but this study involved wearable devices and is a non-peer-reviewed preprint [39].

Hamdani and Chihi employed simulation-based testing to validate an adaptive HCI model for Industry 5.0 settings and reported measurable improvements in efficiency, fault detection and recovery time, with explicit stress reduction as a design objective [38]. Carrera-Rivera and Larrinaga gave a technical description of how machine

learning based systems can engineer adaptive interfaces by predicting the next required interface elements for a user and displaying them while hiding irrelevant elements [37]. Collectively, these studies provide converging evidence that intuitive, adaptive design is a plausible mechanism for reducing the techno-overload and techno-complexity in AI-integrated work contexts. The causal experimental evidence by Fischer and Riedl showed that instrumental support in the course of technostress-inducing events leads to a faster restoration of task performance, thereby confirming design-embedded support features as high-value productivity interventions [34]. Saleem et al. found that training and creative self-efficacy positively moderate the relationship between technostress and performance [33]. This implies that UCD interventions are most effective when they are combined with company skill-building programs.

Evidence for user feedback involvement spans four decades of IS researchThe most comprehensive evidence base for this dimension was synthesized by Bano and Zowghi who synthesized 87 primary studies and concluded a positive relationship in 52 [40]. Olson and Ives found that formal, structured feedback processes are significantly more effective than informal consultation, while McKeen et al., showed that involvement is most important under high task and system complexity, precisely the conditions of AI-integrated call centers [41,43]. Involvement was shown to predict actual system use and satisfaction, hence a way to productivity [42]. Soyangco et al., provide indirect support for the UCD-productivity relationship in a comparable developing-country BPO setting in the Philippines, finding tools and technology to be a significant predictor of call-center agent productivity (instrument reliability: Cronbach's alpha = 0.967) [1]. The most important empirical gap identified by this review is the lack of any comparable peer-reviewed research on Kenya's BPO sector.

Organizational challenges facing AI-UCD integration in Kenya's BPO sector

The literature identifies four categories of challenges. The first is organizational culture and competing priorities. Gorichanaz identifies five barriers to human-centered design: Single-Minded Arrogance, Competing Visions, Moving Fast and Breaking Things, Pragmatically Getting by and Sidestepping Responsibility [44]. Together, these barriers reflect organizational pressure for speed and a lack of strategic clarity, indicating that AI-UCD integration is challenged more by organizational and political issues than by technical ones. This may be more pronounced in the case of the BPO industry in Kenya where contracts with international clients require a fast turnaround time, leaving little room for deliberate investment in user experience.

The second category concerns resource allocation and leadership capacity. Nair et al. conducted a mixed-methods study in healthcare that classified barriers to AI implementation into twelve conceptual categories and found major structural barriers such as inadequate resources, limited leadership capacity and misaligned change management processes [45]. Winby and Xu developed a five-stage Human-Centered AI Maturity Model (HCAI-MM) to guide organizations' progression in human-centered AI governance, identifying cultural resistance and resource allocation limitations as the main barriers to advancing organizational maturity in human-centered AI governance [46]. Hlatshwayo et al. applied the Technology-Organization-Environment (TOE) framework to South African SMEs and argued that algorithmic bias, data privacy risks and lack of transparency compound existing infrastructure and skills shortages in African organizations, a finding relevant to Kenya's BPO industry [48].

Third, algorithmic surveillance and lack of worker autonomy. Similar patterns of algorithmic management across industries including increased surveillance, increased work pace, reduced autonomy and organized resistance from workers are described by Kellogg et al., [10]. In cross-national case studies of African service sectors, the International Labor Organization identifies job intensification as a risk of algorithmic management [11]. Managers also report confusion about accountability and algorithm opacity. The European Parliamentary Research Service says that failures in governance affect the whole organization [47]. These dynamics structurally limit UCD adoption. Agent monitoring and control systems do not favor this reorientation toward the user.

The fourth category is the operational environment in Africa and its specific ethical and contextual constraints. According to Hlatshwayo et al., important ethical challenges of AI adoption among SMEs in Africa are algorithmic bias, data privacy violations and lack of transparency and frameworks in high-income economies are insufficient [48]. Mdhluli also mentioned the absence of AI design guidance for the South African context, which is likely to be the case for Kenya as well [18]. In their econometric analysis, Giwa and Ngepah found a negative association between AI investment and low-skilled employment in South Africa, showing the socio-economic implications of using AI without sufficient UCD protections [13]. Yam et al., in their multimethod study, showed that exposure to AI causes job insecurity and maladaptive organizational behavior even when there is no actual job displacement [12]. This finding is relevant to the management of call-center agents in Kenya, where AI is being widely implemented.

Strategic directions for future research on AI-driven UCD in Kenya's BPO sector

First, we propose to develop theoretical frameworks for AI-based user-centered design that are contextually relevant to Africa and tested in Kenya. To our knowledge, no peer-reviewed literature exists on AI-UCD in call center environments in Kenya or East Africa and the closest African counterparts (South African studies on SMEs and employee assistance) are quite different in their context. Adopted frameworks from high income countries are not enough for African settings as indicated by Hlatshwayo et al. and Mdhluli [48,18]. According to Chang et al., AI-related stressors can be viewed as challenges or hindrances depending on the individual and situational factors [31]. Hence, the validation of the model for the specific

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country of Kenya is a practical necessity rather than an academic refinement.

The second is the utilization of longitudinal and high-frequency research methods. The most frequently used methods in the reviewed literature, cross-sectional surveys and controlled experiments, cannot capture the daily variations of technostress and productivity in the setting of call-center employment [31]. Technostress can be especially well studied in call center environments using experience sampling and diary studies, because these methods allow for the tracking of intra-individual fluctuations across time intervals. Longitudinal designs will also help us to follow the long-term effects of UCD interventions after initial implementation. This is a major gap in the evidence of how BPO operators manage AI deployments.

The third direction involves incorporating organizational-support structures into AI-UCD technology program design and evaluation. According to Harunavamwe and Ward [49], perceived organizational support had the greatest direct effect on workplace flourishing, explaining 47% of its variance along with technostress and work-family conflict. Saleem et al. [33] found that training and creative self-efficacy moderate the technostress-performance relationship, suggesting that holistic organizational learning frameworks benefit most from UCD interventions. In a resource-constrained developing country, Malik et al., found that perceived organizational support buffered technostress-induced exhaustion [35]. Instead of studying technical features, future AI-UCD studies should combine interface reconfiguration, systematic feedback, flexible job structures and organizational education.

Strength and transferability of the evidence

Table 9 summarizes the four research questions and grades them on two dimensions: evidence strength, based on Table 6 and transferability to Kenyan call centers. Transferability is high for comparable settings (developing-country BPO or service work), moderate for other high-complexity workplaces and low for settings that differ greatly in task, workforce, or institutions.

Finding	Main sources	Evidence strength	Transferability to Kenyan call centers
Adaptive interfaces reduce cognitive load and errors	Montazer & Ahmadi [36]; Hamdani & Chihi [38]; Wang [39]	High	Moderate (non-BPO settings)
Formal user involvement increases system use	Bano & Zowghi [40]; Baroudi et al. [42]; McKeen et al. [43]	High	Moderate (pre-AI IS projects)
Embedded support restores performance after disruption	Fischer & Riedl [34]	High	Moderate
Organizational support and training buffer technostress	Saleem et al. [33]; Harunavamwe & Ward [49]; Malik et al. [35]	Moderate	High (developing-country and African samples)
Tools and technology predict BPO agent productivity	Soyangco et al. [1]	Moderate	High (Philippine BPO)
Algorithmic management intensifies work and reduces autonomy	Kellogg et al. [10]; ILO [11]; EPRS [47]	Moderate	Moderate to high
Barriers to UCD are mainly organizational	Gorichanaz [44]; Nair et al. [45]; Winby & Xu [46]	Moderate	Moderate
AI raises job insecurity among low-skilled workers	Yam et al. [12]; Giwa & Ngepah [13]	High / moderate	High
Imported AI governance frameworks fit African firms poorly	Hlatshwayo et al. [48]; Mdhluli [18]	Moderate	High
AI adoption in Kenyan BPOs is extensive and growing	Callin [14]; Site Selection Group [2]; Outsource Accelerator [15]	Contextual	High (Kenya-specific)

Abbreviations: BPO, business process outsourcing; IS, information systems; UCD, user-centered design.

Table 9: Strength and transferability of the main findings.

Two themes emerge. The strongest evidence, the effects of adaptive interfaces and structured user involvement, was obtained in laboratories, wearable-device studies, industrial simulations and conventional information systems projects, which have the weakest direct link to Kenyan call center. Second, contextual or conceptual sources are used to find Kenya-specific findings on AI adoption and African governance constraints. This mismatch is at the heart of the research gap: Kenyan practitioners have either strong but distant evidence, or close but weak evidence and nothing that is both strong and local. An integrative UCD-JD-R framework for AI-integrated call center.

The synthesis is consolidated in the framework shown in Figure 2. It uses the JD-R model as its backbone and draws on technostress theory, TTF, UTAUT and the appraisal perspective to specify how AI system features become either demands or resources for call-center agents. Without UCD, AI features generate the five technostress creators, namely overload from information saturation, complexity from opaque outputs, invasion from continuous surveillance, insecurity from automation and uncertainty from frequent updates, which deplete agents' energy and reduce productivity through the health-impairment path The same features that increase engagement and productivity along the motivational path with UCD can also provide resources i.e. better task-technology fit, perceived control,

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timely and usable information, built-in support. The strength of each path is determined by organizational support, the intensity of algorithmic monitoring and the Kenyan BPO context. The central argument of this review is that UCD is the design strategy for realizing the resource potential of AI in Kenya's BPO sector.

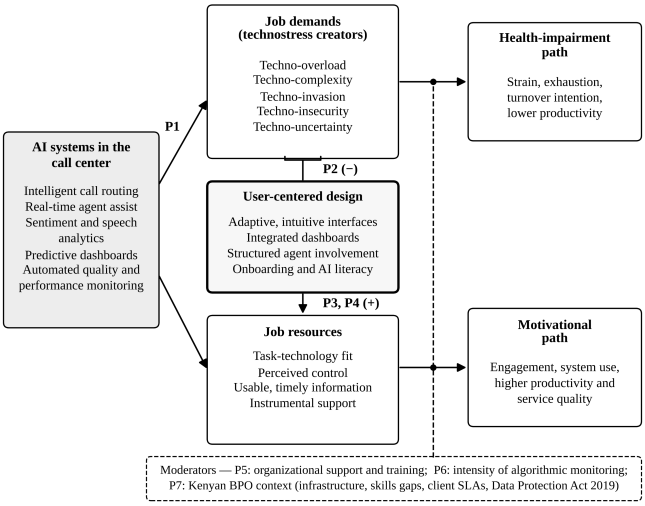


Figure 2: Integrative UCD-JD-R framework for AI-integrated call centers. P1–P7 refer to the propositions in Table 10; dashed lines denote moderating effects. Abbreviations: UCD, user-centered design; JD-R, job demands-resources; BPO, business process outsourcing; SLA, service-level agreement.

The framework makes three theoretical moves. First, UCD is considered not as a distinct outcome, but as a boundary condition for the JD-R processes, weakening the path from AI deployment to technostress creators (P2) and strengthening the path from AI deployment to job resources (P3, P4). Design is thus the point where managerial choices enter the model. Second, it distinguishes two kinds of UCDs. The aspects of the interface-level design (adaptive layouts, integrated dashboards) are mostly about cognitive load and thus techno-overload and techno-complexity. Process-level design, like the way structured agents are involved and onboarded, is mainly affecting acceptance, control and perceived fairness and therefore the motivational pathway. Third, it makes explicit the organizational and institutional context. P5 – Organizational support can compensate for poor design, whereas P6 – Intensive algorithmic monitoring can neutralize good design by turning every interface into a surveillance channel. We introduce the Kenyan context as a moderator (P7) and not background, so that we can test rather than assume context-specific effects.

Table 10 states seven propositions derived from the framework, together with the evidence on which each rest. They are formulated so that they can be tested with agents in Kenyan call centers using established instruments (e.g., the technostress-creator scale of Ragu-Nathan et al. [6] and the NASA Task Load Index) alongside operational productivity data such as average handling time, first-contact resolution and quality scores.

No.	Proposition	Principal supporting evidence
P1	The more extensively AI features are deployed in agent workflows without UCD, the higher agents' technostress creators.	Ragu-Nathan et al. [6]; Nastjuk et al. [7]; Pansini et al. [4]
P2	Adaptive interfaces and integrated dashboards weaken the effect of AI deployment on techno-overload and techno-complexity.	Montazer & Ahmadi [36]; Wang [39]; Hamdani & Chihi [38]
P3	UCD increases task-technology fit and perceived control, which in turn increase engagement and productivity.	Goodhue & Thompson [26]; Scholze & Hecker [30]; Fischer & Riedl [34]
P4	Formal, structured agent involvement in AI design and governance increases AI acceptance and actual use, more so than informal consultation.	Olson & Ives [41]; Baroudi et al. [42]; McKeen et al. [43]; Bano & Zowghi [40]
P5	Organizational support and training buffer the negative effect of technostress on productivity and wellbeing.	Saleem et al. [33]; Harunavamwe & Ward [49]; Malik et al. [35]
P6	The intensity of algorithmic monitoring weakens the positive effects of UCD (P2–P4) by increasing techno-invasion and reducing autonomy.	Kellogg et al. [10]; ILO [11]; EPRS [47]
P7	Kenyan contextual conditions (infrastructure reliability, skills gaps and client-driven service-level pressure) moderate the strength of P2–P5.	Hlatshwayo et al. [48]; Mdhluli [18]; Gorichanaz [44]; Callin [14]
Abbreviations: UCD, user-centered design; AI, artificial intelligence.		

Table 10: Research propositions derived from the integrative framework.

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Discussion

This systematic review of AI-driven UCD in Kenya's BPO call-center sector, based on sources predominantly from 2007 to 2026 and analyzed through the lens of the JD-R model and provisional coding, reveals a field with substantial theoretical promise, robust emerging empirical evidence for critical UCD dimensions and a conspicuous lack of Kenya-specific research. Research on AI-UCD in organizational settings has provided important theoretical and empirical insights on the relationships between AI system design, technostress and employee productivity. However, the field is still fragmented and has not yet matured in the African context. The following subsections address each research question with the JD-R framework as integrating lens.

The theoretical landscape of AI-driven UCD

The common logic of the reviewed theoretical frameworks is that artificial intelligence may be a job demand or a job resource depending on the fit between the system and the task, the individual agent and the organizational environment. The JD-R model is the overarching framework that distinguishes between the health-impairment path, where poorly designed AI induces technostress and the motivational path, where well-designed AI promotes engagement and performance [3,30]. Task-Technology Fit and Person-Environment Fit specify under which conditions AI is perceived as a resource [26,27]. The transactional stress model shows why different agents perceive the same system differently [28]. The technostress creators specify the demands that design must meet [6]. UTAUT links these design conditions to adoption behaviour [29]. Design plays a role in whether technology leads to eustress or distress [8]. But these frameworks have been largely applied in isolation and in high income settings. No integrated model exists yet that explains how AI-UCD affects technostress and productivity in African call center.

Intuitive interface design and agent productivity

The resource pathway of the JD-R model explains how intuitive UI design improves productivity: by reducing the cognitive demands of operating AI-integrated platforms, well-designed interfaces free cognitive resources for customer interaction, problem-solving and high-quality service. The experimental findings of Montazer and Ahmadi, Wang and Hamdani and Chihi provide the clearest evidence of the productivity effects of adaptive design, although none of these studies was conducted in a call center [36,39,38]. Four decades of information systems research suggest that structured, formal involvement of users in system design and governance generally improves system acceptance and use and that effectiveness depends on the type and formality of involvement, rather than its mere presence [41,43]. Well-designed AI tools that adhere to UCD principles can improve agent performance even with the consideration of the demands of AI interaction, especially when agents have access to training and structured organizational support [33]. Soyangco et al., indirectly support the relevance of these results to Kenya's BPO industry, but no study has tested these relationships in a Kenyan call center, limiting confident generalization [1].

Organizational challenges and their systemic nature

The organizational challenges highlighted in this review are all systemic rather than individual and organizational rather than technical. Gorichanaz found that organizational culture and conflicting strategic priorities are causes of UCD failures [44]. Nair et al. identified leadership capacity and change management as structural barriers [45]. Kellogg et al. and the ILO documented that algorithmic management structures are inherently resistant to user-centered reorientation, as surveillance and control are their design goals [10,11]. Overall, the findings indicate that the adoption of AI-UCD in Kenya's BPO industry cannot be achieved through interface redesign alone but rather requires changes at the organizational level that address issues of governance, accountability, leadership commitment and cultural change. Hlatshwayo et al., add the important dimension that these universal challenges are exacerbated by African-specific constraints that require context-specific solutions [48]. The macro-level employment data from Giwa and Ngepah indicates that the ramifications of AI adoption without UCD safeguards extend beyond individual productivity to sector-level employment sustainability [13].

Strategic directions for future research

The strategic directions emerging from this review, Kenya-specific framework development, longitudinal research designs and integrated organizational-technical interventions, reflect the JD-R model's emphasis on context-specific resource provisioning. The persistent absence of Kenya-validated research frameworks means that BPO operators currently making AI deployment decisions are doing so without an evidence base accounting for their specific organizational, workforce and infrastructural context. Chang et al., found that AI stressor dynamics are time-dependent and therefore, cross-sectional work cannot capture the full picture [31]. Harunavamwe and Ward found that organizational support is the dominant predictor of employee flourishing under technostress, implying that purely technical UCD solutions are unlikely to be sufficient [49]. Bridging these research gaps in the future will not only improve theoretical understanding but also provide the empirical basis that Kenya's BPO operators, government policy agencies and international investors need to make evidence-based decisions on AI deployment that protect agent wellbeing and promote sector competitiveness.

Theoretical implications

The review shows that the theories in the field are complementary rather than competing, but have been used in isolation. JD-R explains the two processes through which AI affects agents; technostress theory specifies the demands; TTF and P-E fit explain why the same system has different effects on different agents; and UTAUT explains adoption. The integrative framework brings them together and specifies UCD as the mechanism that moves AI from the demand side

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to the resource side. The review also extends the argument of Tarafdar et al., that design determines eustress or distress by identifying which design features carry the strongest evidence (adaptive interfaces and structured involvement) and which conditions limit them (algorithmic monitoring and contextual constraints) [8]. Finally, the finding by Borle et al. that technostress samples over-represent workers of high socioeconomic position, combined with the absence of Kenyan peer-reviewed studies, suggests that existing models may be biased toward knowledge workers [20]. Testing the propositions with call-center agents would therefore also test the boundary conditions of technostress theory.

The findings also qualify earlier reviews. Pansini et al., concluded that design-level resources are under-explored; this review shows that experimental evidence on such resources does exist but is scattered across HCI, industrial engineering and information-systems research that technostress reviews have rarely drawn on [4]. Rohwer et al., reported a shortage of research on preventing technostress; adaptive interfaces and structured involvement are precisely preventive measures, acting before strain arises rather than helping workers cope afterwards [17]. Mdhluli concluded that there is no contextually appropriate AI guidelines for design in South Africa [18]. The present review finds the same gap in Kenya and adds that the only local evidence in the BPO sector is commercial, rather than scholarly.

Implications for practice and policy

A holistic strategy to tackling the ubiquity of technostress at both the individual and organizational levels is essential in AI-integrated BPO call centers in Kenya. Based on the findings of this review, the following procedures and possible remedies for the management of AI-driven technostress are identified:

I. Focus on intuitive, adaptive AI interfaces that modify the complexity to the individual agent's competence and workload state, thus reducing techno-overload and techno-complexity, the most direct productivity-damaging technostress creators [36,38].

II. Establish formal, structured channels for agent feedback within AI platform governance, not merely informal consultation, to improve system acceptance, actual use and agent ownership of AI tools [40,41,43].

III. Counter techno-uncertainty and create the enabling conditions for uptake by deploying AI training and AI-literacy programs with every AI deployment [29,33].

IV. Develop and implement guidance for AI-UCD in specific sectors adapted to the Kenyan BPO infrastructure, workforce and regulatory environment, instead of assuming that frameworks developed in other contexts will transfer [18,48].

V. Use human-centered AI maturity models as a governance framework to develop organizational capacity for responsible AI-UCD integration over time [46].

VI. Monitor agent wellbeing, technostress levels and productivity throughout the AI deployment phases using validated instruments and use findings to iteratively refine both interface design and organizational support structures [6,49].

VII. Limit algorithmic monitoring to what is necessary and make metrics for performance transparent to the agents, thus reducing techno-invasion [10,11].

The review highlights the need for sector-specific guidance on human-centered AI in BPO operations for policy makers and industry bodies. Such guidance must be consistent with Kenya's Data Protection Act which governs the processing of personal data including data generated through monitoring of employees and recording of customer interactions [51]. Guidance developed in partnership with operators, agents and researchers would help ensure that the growth of AI-enabled outsourcing in Kenya is compatible with decent work.

Research agenda

Table 11 translates the three research directions identified under the fourth research question into specific studies, linked to the propositions in Table 10.

Priority	Example research question	Suggested design	Propositions
1. Establish the baseline	How prevalent are the five technostress creators among Kenyan call-center agents and which AI features are associated with them?	Multi-site survey with validated scales linked to operational data	P1, P7
2. Test design effects	Do adaptive interfaces reduce cognitive load and improve handling time and quality for Kenyan agents?	Field or lab experiment with NASA-TLX and productivity metrics	P2, P3
3. Test involvement effects	Does formal agent involvement in AI governance increase actual system use and engagement?	Quasi-experiment across teams or sites	P4
4. Capture dynamics	How do technostress and productivity fluctuate within and across shifts after an AI rollout?	Experience-sampling or diary study; multi-wave panel	P1–P3
5. Test boundary conditions	Do organizational support and monitoring intensity change the effects of UCD?	Multilevel survey (agents nested in teams)	P5, P6
6. Build a Kenyan framework	Which design and governance principles do agents, managers and clients consider essential?	Qualitative interviews and Delphi study	P7
Abbreviations: NASA-TLX, NASA Task Load Index; P, proposition.			

Table 11: Prioritized research agenda for AI-driven UCD in Kenya's BPO sector.

Research trends in AI-driven UCD and technostress

AI-driven UCD in organizational contexts is a developing field that has accelerated substantially since 2020. Through comprehensive analysis of the 39 sources included in this review, four distinct research trends were identified.

Expansion of the JD-R framework to AI and digital work

Researchers increasingly use the JD-R model to understand the demands and resources associated with digital technologies and AI systems. Digital job demands and digital job resources have been conceptualized as distinct constructs and the model's validity as a lens for technostress has been confirmed by more than a decade of empirical research [4,30]. This extension of the JD-R model to AI is arguably one of the most important theoretical developments in the field since the technostress-creator framework [6].

Growing focus on AI-specific stressors and adoption outcomes

Studies increasingly distinguish general technostress from AI-specific stressors, recognizing that algorithmic supervision, fear of job loss and AI opacity produce distinct stress experiences that existing instruments were not designed to measure. Chang et al., developed and tested a typology of AI challenge and hindrance stressors with opposing effects on adoption intention, while Wang and Wang validated a dedicated Artificial Intelligence Anxiety Scale [31,32]. This trend reflects growing recognition that AI is a qualitatively different technological environment that requires new measurement instruments and theoretical models.

Contextualization in developing-country and African settings

Research increasingly treats the African organizational context as a distinct setting that requires its own frameworks, rather than assuming that findings from high-income economies apply universally. Mdhluli, Hlatshwayo et al., Harunavamwe and Ward and Giwa and Ngepah together lay the groundwork for AI and technostress research in Africa, while showing that current evidence is insufficient for context-specific guidance [18,48,49,13]. This trend creates the empirical and theoretical preconditions for Kenya-focused BPO research to emerge as a distinct and urgently needed area within the technostress and AI-UCD literature.

Methodological diversification toward causal and longitudinal designs

Controlled experiments multi-wave time-lagged surveys and multimethod designs are increasingly being used to strengthen causal inference in a field that was previously dominated by cross-sectional self-report designs [34,36,31,12]. Such diversification of methods is particularly consequential for the AI-UCD domain, where causal links between interface design choices and productivity outcomes are needed to develop actionable practice guidance for Kenya's BPO sector.

Limitations

Several limitations should be noted. First, only English-language sources available up to mid-2026 were included, so relevant work in other languages or published later may be missing. Second, the scarcity of peer-reviewed Kenyan evidence meant that industry and policy reports had to be used to describe the local context; these were weighted as contextual and were not used as evidence of causal relationships. Third, the experimental studies of adaptive interfaces come from settings other than call centers, so their transfer to Kenyan BPOs is inferred rather than demonstrated; the propositions in Table 10 are offered to test that inference. Fourth, the number of included sources (39) is modest, which reflects the novelty of the topic but limits the possibility of quantitative synthesis. These limitations do not alter the main conclusions but should be considered when applying them in specific organizations.

Summary

The analysis was based on 39 references from theory, empirical and industry literature. The analytical framework was the JD-R model and provisional coding. The strategies and interventions proposed in this study can help individuals and organizations to ethically implement AI-UCD and to create a positive relationship between call-center agents and artificial intelligence (AI) systems in the BPO industry in Kenya.

The review concluded that the JD-R model, Task-Technology Fit, Person-Environment Fit, transactional stress model and the framework of technostress creators and UTAUT provide a theoretically sound but structurally fragmented basis for the exploration of AI-driven UCD, for the first research question. This is both a theoretical gap and a practical bottleneck. There is no unified framework for AI-powered call centers in Africa.

In relation to the second research question, the analysis showed that there was the strongest evidence base for intuitive user interface design and particularly for adaptive interface design. There is a wealth of empirical evidence that shows reductions in cognitive load, error rates and hesitation as well as improvements in performance. Evidence on user feedback involvement, accumulated over four decades of research, is mostly positive but depends on how formalized and structured the involvement methods are. There is evidence that both UCD dimensions affect productivity in similar BPO and high-complexity ICT environments, but neither has been tested directly in Kenyan call centers.

In relation to the third research question, the review revealed that the main constraints to AI-UCD integration in Kenya’s BPO sector are organizational and structural challenges, not technical ones. These include cultural resistance, resource and leadership capacity gaps, algorithmic surveillance structures resistant to user-centered reorientation and African context-specific constraints including

infrastructure limitations, skills gaps and the inadequacy of imported governance frameworks.

The review revealed three high-level strategic directions in the fourth research question: development of Kenya-validated AI-UCD frameworks; adoption of longitudinal and high-frequency research designs; and testing of integrated organizational-technical interventions, embedding interface design within broader organizational support and governance structures. To summarize, the paper argues that rapid convergence of AI adoption, well supported but geographically dispersed UCD research and the complete absence of Kenya-specific evidence creates a substantial and urgent gap that warrants and directs empirical investigation in this context. Future research should explore the impact of emerging AI capabilities, such as large language models and autonomous agent systems, on technostress dynamics in call-center environments.

The review's contribution lies in combining these findings into an integrative UCD–JD-R framework with seven testable propositions, a quality-weighted map of the evidence and a prioritized research agenda. Together they show where the evidence is strong, where it is merely suggestive and what must be tested in Kenyan call centers before confident guidance can be given to the sector's operators, policymakers and investors.

Conclusions

The review finds that AI in Kenya's BPO call centres is not an inherent burden or benefit to agents: whether it is a job demand or a job resource depends on its design, deployment and support. User-centered design, particularly with adaptive interfaces and formal and structured agent involvement, offers the most promising path to making AI a resource. This is contingent on organizational support and is undermined by intensive algorithmic monitoring. The combination of growing AI adoption documented but geographically remote UCD research and a missing evidence base for Kenya, presents a major and urgent gap that justifies and directs empirical research in this setting.

The review contributes by combining these findings into an integrative UCD-JD-R framework, which includes seven testable propositions, a quality-weighted map of the evidence and a prioritized research agenda. Together they map the strong and suggestive evidence and what needs to be tested in Kenyan call centers to provide confident guidance to operators, policymakers and investors in the sector.

In practice, BPO operators should see UCD as an organizational commitment rather than a technical add-on, combining adaptive interfaces with agent training, structured feedback channels and transparent, proportionate monitoring. At the level of research, the key priority is to test the seven propositions with Kenyan call center agents in longitudinal and experimental designs with special attention to emerging capabilities such as large language models and autonomous agent systems. Fulfilling these priorities will help ensure AI supports agent well-being and the competitiveness of Kenya's BPO sector.

Author contributions

F.M.O.: conceptualization, search, screening, analysis, writing – original draft; P.W.K. and G.C.: supervision, methodology, writing – review and editing.

Data availability

The data extraction sheet for the 39 included sources is available from the corresponding author on reasonable request.

Use of AI-assisted tools

Quill Bot and paper pal were used to improve grammar and coherence. The authors reviewed and edited all content and take full responsibility for the manuscript.

Conflict of interest

The author declares no conflict of interest.

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