

Primary Technostress Factors and Employee Productivity in AI Business Process Outsourcing: Evidence from Kenya

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Abstract

Business Process Outsourcing (BPO) firms in developing economies have adopted artificial intelligence (AI) and digital platforms at a pace that has outrun the organisational and human resources needed to absorb them, producing technostress – stress arising from the use of information and communication technologies. This study examined the effect of three primary technostress factors – technology factors, organisational factors and individual response factors – on employee productivity among BPO workers in Kenya. A sequential explanatory mixed-methods design was used. Quantitative data were collected from 368 employees (99.7% response rate) across 14 BPO providers in Nairobi using a validated, piloted questionnaire, and analysed with multiple linear regression in SPSS; qualitative data were collected through semi-structured interviews and focus group discussions with 15–20 purposively selected employees and analysed thematically in NVivo. The three factors jointly explained 4.5% of the variance in productivity ($R^2 = .045$), $F(3, 364) = 5.685$, $p = .001$. Organisational factors ($\beta = 0.137$, $p = .010$) and individual response factors ($\beta = 0.172$, $p = .001$) were significant positive predictors, whereas technology factors alone were not ($\beta = -0.046$, $p = .390$). Interview participants described technology overload and unexplained system changes as stressful but attributed their effect on productivity to the presence or absence of training, technical support and employee involvement. The findings support the Job Demands-Resources model and Task-Technology Fit theory and suggest that BPO managers seeking to protect productivity under AI-driven digitalisation should prioritise organisational support and employee coping resources rather than technology alone.

1. Introduction

The diffusion of artificial intelligence (AI) and cloud-based digital platforms into Business Process Outsourcing (BPO) operations has been presented as a route to efficiency, yet a growing body of evidence suggests it is also a source of chronic occupational stress (Tarafdar et al., 2019; Whelan et al., 2022). Technostress – stress that results from an individual's efforts to deal with constantly changing information and communication technologies (ICT) – has been linked to reduced job satisfaction, burnout, and lower productivity across sectors as varied as banking, education and healthcare (Porcari et al., 2023; Bourlakis et al., 2023; Kaltenecker et al., 2024). In BPO call centres, where employees interact with customer relationship management (CRM) systems, automated call routing, monitoring dashboards and, increasingly, AI-based assistance tools for the duration of every shift, the conditions that produce technostress are close to continuous. Kenya's BPO sector has grown rapidly on the strength of government digital-economy policy and relatively low labour costs, and now employs tens of thousands of workers in Nairobi alone

(Kleibert and Mann, 2020; Mann and Graham, 2021). Existing technostress research, however, remains concentrated in developed economies or in adjacent sectors such as telecommunications and higher education (Jimmy et al., 2023; Olorunfemi and Adekoya, 2023), and rarely disaggregates the technology-related, organizational and individual-level contributors to the stress that AI-integrated work imposes on employees. Where BPO-specific studies exist, they seldom combine statistical evidence of the technostress–productivity relationship with an explanation, from employees themselves, of why particular factors matter more than others (Dutta and Mishra, 2024). This leaves BPO managers in Kenya and comparable developing-country contexts with limited evidence-based guidance on where to direct scarce resources: toward technology redesign, toward organizational support structures, or toward building employees' individual coping capacity.

This study addresses that gap by examining, through a sequential explanatory mixed-methods design, how three primary technostress factors – technology factors, organisational factors and individual response factors – relate to employee productivity among BPO workers in Kenya's AI-integrated call centres. The technology factors capture the demand side of the technostress literature: overload, complexity, invasion and uncertainty attributable to digital systems themselves (Tarafdar et al., 2007; Ragu-Nathan et al., 2008). The organisational and individual response factors capture the resource side: training, leadership, workload realism and IT support on the one hand, and coping strategies, stress appraisal and work-life balance on the other (Bakker and Demerouti, 2007; Lazarus and Folkman, 1987). Framing all three within a single regression model, rather than studying technology stressors in isolation, allows their relative contribution to productivity to be compared directly – a comparison that is largely absent from the existing BPO literature.

Beyond its BPO focus, the study speaks to a wider question in the information systems literature: whether interventions aimed at reducing technostress should target the technology itself or the organisational and individual context in which it is used. Much of the practitioner discourse around AI adoption emphasises interface redesign and change-management communication – technology-side interventions. If, as this study investigates, technology factors are not the binding constraint on productivity once organisational and individual resources are accounted for, then technology-side interventions alone would be predicted to have limited productivity impact, with resource-side interventions offering a larger return. Testing this proposition with sample-level regression evidence, corroborated by employees' own explanations of the mechanism, is the specific contribution this paper makes to that debate.

Understanding this distinction matters for a further reason specific to the BPO industry: labour costs and productivity are the principal basis on which outsourcing contracts are priced and renewed, so a productivity effect attributable to preventable organisational under-investment, rather than to the technology itself, is a finding with direct commercial as well as academic relevance to the firms and client organizations that depend on Kenya's BPO workforce.

The remainder of the paper is organised as follows. Section 2 reviews the technostress literature and the theoretical foundations – Task-Technology Fit (TTF) and the Job Demands-Resources (JD-R) model – that motivate the study's hypotheses. Section 3 describes the mixed-methods design, sample, instruments and analytical procedure. Section 4 reports the quantitative and qualitative results. Section 5 discusses the findings in relation to theory and prior evidence, and Section 6 concludes with the study's contributions, limitations and directions for future research. The study contributes, first, a rare developing-country, AI-integrated BPO test of the joint and relative effects of technology, organisational and individual response factors on productivity; second, a theoretical account, combining TTF and JD-R, of why technology factors alone were not a significant predictor of productivity in this setting although organisational and individual factors were; and third, qualitative evidence that explains this pattern in participants' own terms, which is of direct practical value to BPO managers deciding where to invest limited technostress-mitigation resources.

2 Literature review and hypothesis development

2.1 Technostress in the digital workplace

Technostress was defined by Tarafdar et al. (2007) as stress experienced by end users as a consequence of their use of ICT, and operationalised through five creators: techno-overload, techno-complexity, techno-invasion, techno-insecurity and techno-uncertainty (Ragu-Nathan et al., 2008). Subsequent research has extended the construct from personal computing to mobile, cloud and AI-enabled systems, and has consistently linked technostress creators to reduced performance, lower job satisfaction, and higher turnover intention (Tarafdar et al., 2015; Whelan et al., 2022; Nastjuk et al., 2024). Rutkowski and Saunders (2018) describe how the "always-on" nature of modern information systems compounds emotional and cognitive overload, a description that maps closely onto the shift-based, continuously monitored environment of a BPO call centre. In such settings, employees are simultaneously expected to navigate multiple software systems, respond in real time to customers, and meet quantitative performance targets, conditions that Pullins et al. (2020) identify as particularly conducive to technostress among customer-facing sales and service staff.

Comparative evidence from adjacent sectors and regions illustrates both the breadth and the context-specificity of technostress effects. Porcari et al. (2023) validated a Work-Related Technostress Questionnaire in the Italian banking sector and linked technostress to burnout and reduced well-being; Jimmy et al. (2023) found that techno-overload and techno-complexity significantly affected well-being among Malaysian telecommunications employees; and Kaltenecker et al. (2024) reported prospective associations between workplace technostress and burnout symptoms in a longitudinal European sample. In Africa, Olorunfemi and Adekoya (2023) documented technostress among Nigerian university librarians, with gendered differences in reported stress levels, while Dutta and Mishra (2024) showed that the organisational home-work interface moderates the relationship between technostress and workplace stress. Few of these studies, however, examine BPO call centres directly, and fewer still are situated in East Africa, where the combination of rapid AI adoption, infrastructural constraints and a young, digitally engaged workforce creates conditions that may differ from those documented elsewhere (Kleibert and Mann, 2020).

2.2 Theoretical foundations: Task-Technology Fit and the Job Demands-Resources model

Task-Technology Fit (TTF) theory holds that information technology has a positive effect on individual performance only to the extent that its functionality matches the tasks the user must perform (Goodhue and Thompson, 1995). Where fit is poor—where a CRM system is difficult to navigate, where automated workflows do not match the actual sequence of a customer interaction, or where frequent updates change interfaces without adequate explanation—employees must expend additional cognitive effort simply to complete routine tasks, which TTF predicts will show up as reduced performance quite apart from any direct measure of stress (Ayyagari, 2012; Vendramin et al., 2021a). Applied to technostress, TTF suggests that technology factors such as complexity and uncertainty act on productivity primarily through the mismatch they create between system design and task requirements, a mismatch that is, at least in principle, correctable through better system design or user-centered implementation.

The Job Demands-Resources (JD-R) model offers a complementary account that extends beyond the technology itself. Bakker and Demerouti (2007) distinguish between job demands—aspects of work that require sustained physical or psychological effort, such as technology-induced workload, role ambiguity and time pressure—and job resources—aspects of work that help employees achieve goals, reduce demands, and stimulate growth, such as supervisor support, training, autonomy and feedback. The model predicts that demands drive strain (and, ultimately, reduced performance) through an energy-depletion process, while resources buffer that strain and can independently motivate performance through a motivational process (Bakker et al., 2023). Mapped onto this study, technology factors correspond most directly to job demands, while organizational factors (leadership, training, workload realism, IT support) and, at the individual level, coping resources and work-life balance correspond to job resources and to the personal resources that determine how effectively an employee converts organizational resources into reduced strain (Lazarus and Folkman, 1987).

The JD-R model thus predicts that the productivity effect of technology demands should be attenuated, and potentially rendered statistically indistinguishable from zero, once organizational and individual resources are entered into the same model – a prediction directly tested in this study.

2.3 Technology factors and employee productivity

Technology factors in this study comprise techno-overload (pressure to work faster because of digital tools), techno-complexity (difficulty learning and using CRM and workflow systems), techno-invasion (intrusion of technology into personal time) and techno-uncertainty (stress from continual system changes). A substantial body of work associates these creators with reduced performance: Tarafdar et al. (2007) found that technostress creators increased role stress and reduced productivity among knowledge workers, and Ayyagari (2012) linked information overload and poor task-technology fit directly to technostress. In BPO and comparable service environments, where agents must operate several concurrent systems under continuous supervision, these effects might be expected to be especially pronounced (Pullins et al., 2020; Rutkowski and Saunders, 2018). On this basis, technology factors were hypothesised to significantly predict employee productivity in Kenya's AI-integrated BPO sector.

H1a. Technology factors have a statistically significant effect on employee productivity.

2.4 Organisational factors and employee productivity

Organisational factors in this study comprise training adequacy, leadership and organizational culture, realism of workload expectations, fatigue-mitigation practices, and the availability of technostress-specific support such as IT helpdesks. These map onto the resource side of the JD-R model: Bakker and Demerouti (2007) show that job resources such as supervisor support and training buffer the impact of job demands on strain and sustain performance even under high workload. Saleem and Malik (2023) found that quality-of-work-life factors moderated the relationship between technostress and job performance, and Kaltenecker et al. (2024) linked organizational support to lower burnout under technostress. Because organisational resources are, in principle, within management control and can be strengthened independently of the technology itself, they were hypothesized to be a significant predictor of productivity.

H1b. Organisational factors have a statistically significant effect on employee productivity.

2.5 Individual response factors and employee productivity

Individual response factors comprise employees' cognitive appraisal of technology demands, their coping strategies (problem-focused and emotion-focused), their ability to maintain work-life boundaries, and the effect of these on job satisfaction. The Transactional Model of Stress and Coping (Lazarus and Folkman, 1987) holds that the experience of stress, and its consequences for performance, is determined not only by the objective demand but by how the individual appraises and copes with it; two employees facing the same system complexity may therefore experience very different productivity effects depending on their coping resources. This individual-differences account is consistent with Person-Environment Fit theory, which frames well-being and performance as a function of the match between an employee's abilities and the demands of the environment.

Prior technostress studies have found that coping strategies and stress appraisal significantly predict performance outcomes independent of the objective level of technology demand (Saleem and Malik, 2023). Individual response factors were therefore hypothesised to significantly predict productivity.

H1c. Individual response factors have a statistically significant effect on employee productivity.

2.6 Conceptual model

Figure 1 summarizes the conceptual model: technology factors, organizational factors and individual response factors are modelled as three simultaneous predictors of employee productivity, consistent with TTF's account of technology-task mismatch and JD-R's account of demands and resources operating together rather than in isolation. Because JD-R predicts that resources can offset demands, the model does not assume that all three factors will be equally, or even significantly, associated with productivity once considered jointly; it is this joint, relative test – rather than three separate bivariate tests – that the present study was designed to provide.

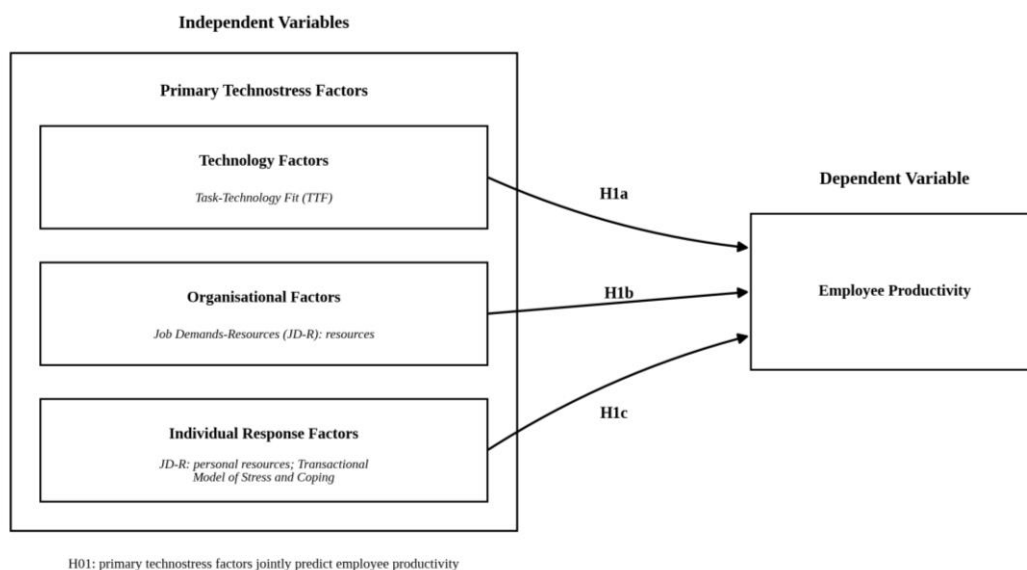


Figure 1. Conceptual model of study.

H1a, H1b and H1c denote the component-level hypotheses tested by the same simultaneous multiple regression model; H01 denotes the omnibus (joint) hypothesis.

2.7 Comparative evidence and the research gap

Table-level comparisons across the technostress literature reinforce the case for jointly modelling technology, organisational and individual factors rather than studying them in isolation. Studies that examine technology factors alone, without organisational or individual controls, tend to report larger, more consistently significant technology-productivity associations (Tarafdar et al., 2007; Ayyagari, 2012); studies that include organisational or individual variables alongside technology factors, by contrast, more often find that the technology coefficient shrinks or loses significance once resources are entered (Saleem and Malik, 2023; Kaltenecker et al., 2024), a pattern consistent with the JD-R account that resources absorb, rather than eliminate, the demand. Very few of these studies, however, are set in a BPO call-centre environment, and none of those identified in this review examine an AI-integrated Kenyan BPO context specifically. This leaves open the empirical question of whether the demand-absorption pattern documented elsewhere in the technostress literature also holds in a developing-country BPO setting characterised by lower average IT infrastructure maturity, a younger workforce, and comparatively recent large-scale AI adoption (Kleibert and Mann, 2020; Mann and Graham, 2021). The present study addresses this gap directly.

2.8 The Kenyan BPO context

Kenya's BPO sector has expanded under the government's digital-economy agenda, positioning Nairobi as a regional hub for voice and non-voice outsourced services (Kleibert and Mann, 2020). This growth has been accompanied by rapid adoption of AI-enabled tools – automated call routing, chatbots, predictive analytics for workforce management, and AI-assisted quality monitoring – often introduced with limited local piloting or change-management capacity relative to firms in more mature outsourcing markets (Mann and Graham, 2021). Employees in this setting are simultaneously exposed to global best-practice technology stacks and to organizational structures still developing the training, IT-support and leadership capacity that the JD-R model identifies as the resources needed to offset technology demands. This combination – high-intensity technology exposure alongside developing organizational infrastructure – makes Kenya's BPO sector an informative, and arguably a hard, test of whether organisational and individual resources are sufficient to offset technology demands, since the resource side of the JD-R equation cannot be taken for granted in the way it might be in a more mature outsourcing economy.

Organisational-resource research outside the BPO sector offers a further point of comparison. Kaltenecker et al. (2024), in a longitudinal European sample, found that perceived organizational support reduced the prospective association between technostress and burnout, while Bourlakis et al. (2023) reported that technostress affected employee performance in educational settings partly through its erosion of perceived organisational support over time. Both studies used repeated measures, which the present cross-sectional design cannot replicate, but both are consistent with the JD-R prediction tested here: that resources, not the raw level of technology demand, determine whether stress translates into impaired functioning. On the individual side, coping research following Lazarus and Folkman (1987) distinguishes problem-focused coping (directly addressing the source of stress, for example by seeking training) from emotion-focused coping (managing the emotional response to stress); BPO employees interviewed for this study described both strategies, with problem-focused coping – asking colleagues or supervisors for help with unfamiliar systems – described more often as effective for maintaining output than emotion-focused strategies such as simply "pushing through" a difficult shift.

2.9 Measuring productivity in a BPO context

Employee productivity in BPO call centres is often operationalised through objective metrics such as average handling time, calls resolved per shift, or adherence to service-level agreements. The present study instead used a self-reported productivity scale capturing perceived task completion, work quality and efficiency, a choice consistent with the technostress literature's general reliance on self-report for both predictor and outcome variables (Tarafdar et al., 2015; Porcari et al., 2023), and necessary because objective, system-logged performance metrics were not made available by participating organizations for confidentiality reasons. Self-reported productivity measures correlate meaningfully, if imperfectly, with supervisor-rated and system-logged performance in prior organizational research, and their use here is treated as a limitation to be addressed, where possible, in future replications with access to objective performance data (see Section 5).

2.10 Summary and hypotheses

Taken together, the literature reviewed above supports three specific, testable hypotheses – H1a, H1b and H1c – nested within a single omnibus hypothesis, H01, that the three primary technostress factors jointly affect employee productivity. TTF provides the theoretical basis for expecting technology factors to matter (H1a); JD-R provides the theoretical basis for expecting organisational factors, as job resources, to matter (H1b); and the Transactional Model of Stress and Coping, together with Person-Environment Fit theory, provides the theoretical basis for expecting individual response factors to matter (H1c). Because JD-R further predicts that resources can offset demands when both are modelled together, the joint test conducted in this study – rather than three independent bivariate tests – is the appropriate way to evaluate whether, in this particular AI-integrated BPO setting, that offsetting effect is strong enough to render the direct technology effect statistically non-significant, as Sections 4 and 5 go on to examine.

3 Materials and methods

3.1 Research design

The study adopted a sequential explanatory mixed-methods design (Creswell and Creswell, 2018): a quantitative phase, in which a cross-sectional survey was used to test the relationship between primary technostress factors and employee productivity, was followed by a qualitative phase of semi-structured interviews and focus group discussions designed to explain the quantitative results. The pragmatist paradigm underlying this design treats quantitative and qualitative evidence as complementary rather than competing, appropriate where the research problem – why particular technostress factors matter more than others for productivity – requires both measurement of effect sizes and explanation of mechanism.

3.2 Population and sampling

The accessible population comprised approximately 9,000 employees across BPO service providers operating in Nairobi, Kenya. Using the Krejcie and Morgan (1970) table for determining sample size, a sample of 369 was drawn, proportionately allocated across 14 participating organizations using stratified random sampling, with strata defined by organization and, within organization, by department. Of the 369 questionnaires distributed, 368 were completed and returned, a response rate of 99.7%. For the qualitative phase, 15–20 employees were purposively selected from among survey respondents based on their direct, sustained interaction with AI-enabled workplace systems, to ensure information-rich accounts of the phenomena under investigation.

3.3 Instrumentation

The quantitative instrument was a structured, self-administered questionnaire adapted from validated scales, including the Technostress Creators and Inhibitors Scale (Tarafdar et al., 2007, 2015) for technology factors and elements of the Work-Related Technostress Questionnaire (Porcari et al., 2023) for symptom and productivity items. The instrument was reviewed by the researcher's supervisors and by subject-matter experts in information systems and organizational psychology for content validity and piloted with 37 respondents (10% of the sample) at one participating organization. Cronbach's alpha coefficients for all constructs exceeded the 0.70 threshold conventionally regarded as acceptable for internal-consistency reliability (Nunnally and Bernstein, 1994), and Kaiser-Meyer-Olkin (KMO) values ranged from 0.65 to 0.84, with Bartlett's test of sphericity significant at $p < .001$ for every construct, supporting the construct validity of the scales used.

Items measuring technology factors, organisational factors and individual response factors were interspersed with, rather than grouped immediately before, the productivity items, a further procedural safeguard against common method bias recommended by Podsakoff-style guidance on survey-design remedies, alongside the statistical Harman check reported in Section 4.1. The qualitative instrument was a semi-structured interview guide developed around the study's objectives and theoretical foundations, covering employees' experiences of technology-related demands, their perceptions of organisational support, and their individual coping strategies. Interviews and focus group discussions lasted approximately 45–60 minutes, were conducted in English or Swahili according to participant preference, and were audio-recorded with consent, transcribed verbatim and anonymised prior to analysis.

3.4 Data collection procedure

Quantitative data collection took place over a 6–8-week period. Research assistants were stationed at participating BPO facilities during shift changes to distribute questionnaires, explain the study's purpose, and obtain informed consent; an online version was also distributed via company e-mail with weekly reminders. Qualitative data collection followed the quantitative phase, so that the interview guide could be informed by the statistically significant relationships identified in the first phase, consistent with the sequential explanatory design.

3.5 Measures

Technology factors, organisational factors and individual response factors were each measured with multiple Likert-type items (5-point scales) and combined into composite scores through the measurement procedures described in Section 3.3. Employee productivity was measured with a multi-item scale capturing self-reported task completion, work quality and efficiency. All composite scores were checked for normality, linearity, homoscedasticity, multicollinearity and the absence of influential outliers prior to regression analysis; variance inflation factors for all three predictors were within conventional limits ($VIF < 3$), indicating that multicollinearity was not a concern.

3.6 Analytical procedure

Quantitative data were analysed in SPSS using descriptive statistics, Harman's single-factor test for common method bias, and multiple linear regression, with employee productivity regressed simultaneously on technology factors, organisational factors and individual response factors. The null hypothesis (H01) that primary technostress factors have no statistically significant effect on employee productivity was tested at $\alpha = 0.05$; component hypotheses H1a–H1c were evaluated from the standardised coefficients of the same model. Qualitative data were analyzed thematically in NVivo following the six-phase procedure of Braun and Clarke: familiarization, initial coding, theme generation, theme review, theme definition, and write-up, with codes generated both deductively from the study's objectives and inductively from participants' own accounts. Quantitative and qualitative results were integrated at the interpretation stage through a joint display comparing statistical results with qualitative themes (Guetterman et al., 2015).

3.7 Ethical considerations

Ethical clearance was obtained from the National Commission for Science, Technology and Innovation (NACOSTI) and the university's Institutional Review Board prior to data collection. Participation was voluntary, informed consent was obtained from all participants, and confidentiality was maintained by removing personal identifiers and storing data on password-protected, encrypted devices accessible only to the research team.

3.8 Validity and reliability safeguards

Beyond the pilot-study reliability and validity checks reported in Section 3.3, construct validity was further supported by exploratory factor analysis of each scale prior to the main analysis: all items loaded on their intended factor above the conventional 0.40 threshold, and no item exhibited a cross-loading above 0.32. Content validity was strengthened by expert review from information systems, human-computer interaction and organisational psychology specialists, who evaluated each item for relevance to the technostress and productivity constructs being measured in an AI-integrated BPO context specifically, rather than relying solely on the face validity of scales developed in other sectors. Because the analysis draws on self-reported cross-sectional data, common method bias was treated as a specific threat to validity and addressed both procedurally, through anonymity and the separation of predictor and outcome item blocks in the questionnaire, and statistically, through the Harman single-factor test reported in Section 4.1.

3.9 Sample size adequacy and generalisability considerations

The realised sample of 368 exceeds the 369 target calculated from the Krejcie and Morgan (1970) table by only one short of the full target, giving the

regression model (three predictors, $N = 368$) statistical power well above conventional thresholds (power $> .99$ to detect the observed effect size at $\alpha = .05$, calculated post hoc using Cohen's $f^2 = .047$). Stratified allocation across 14 organisations, rather than convenience sampling from a single employer, was adopted specifically to support generalization of the results across Nairobi's BPO sector rather than to any single firm's idiosyncratic technology stack or management practice, although, as discussed in Section 5, generalisation beyond Nairobi requires caution.

3.10 Analytic assumptions

Prior to interpreting the regression coefficients, the data were screened for the assumptions underlying ordinary least squares estimation. Histograms and Q-Q plots of the standardized residuals indicated an approximately normal distribution; a scatterplot of standardized residuals against predicted values showed no discernible pattern, supporting linearity and homoscedasticity; and, as reported in Section 3.5, variance inflation factors below 3 for all three predictors indicated that multicollinearity did not materially distort the standard errors of the coefficients reported in Section 4.

Items measuring technology factors, organisational factors and individual response factors were interspersed with, rather than grouped immediately before, the productivity items, a further procedural safeguard against common method bias recommended by Podsakoff-style guidance on survey-design remedies, alongside the statistical Harman check reported in Section 4.1.

4 Results

4.1 Sample characteristics and preliminary analysis

Of the 368 valid respondents, the sample spanned a range of ages, education levels, departments and tenures typical of Kenya's BPO workforce (see Table 1). Harman's single-factor test, conducted as a preliminary check for common method bias, showed that the first unrotated factor explained 27.3% of total variance, well below the 50% threshold conventionally used to flag a common-method-bias concern, indicating that such bias was unlikely to materially affect the results.

4.2 Regression results

A multiple linear regression was conducted to assess the joint effect of technology factors, organisational factors and individual response factors on employee productivity. The overall model was statistically significant, $F(3, 364) = 5.685$, $p = .001$, and explained 4.5% of the variance in employee productivity ($R = .212$, $R^2 = .045$, adjusted $R^2 = .037$). Table 2 presents the standardised and unstandardised coefficients for each predictor.

Organisational factors ($\beta = 0.137$, $t = 2.585$, $p = .010$) and individual response factors ($\beta = 0.172$, $t = 3.240$, $p = .001$) were statistically significant positive predictors of employee productivity. Technology factors, by contrast, were not a statistically significant predictor when entered alongside the other two ($\beta = -0.046$, $t = -0.861$, $p = .390$). On this basis, the omnibus null hypothesis ($H01$) was rejected – the three primary technostress factors jointly and significantly predicted employee productivity – while the component result was mixed: $H1b$ and $H1c$ were supported, but $H1a$ (technology factors) was not.

4.3 Diagnostic checks

Residual diagnostics supported the appropriateness of the regression model. The Durbin-Watson statistic fell within the conventionally acceptable range (1.5–2.5), indicating that residuals were independent; Levene's test indicated homogeneity of error variances across predictor levels ($p > .05$); and inspection of standardised residuals and Cook's distance identified no unduly influential cases.

4.4 Qualitative findings

Thematic analysis of the interview and focus group data produced a theme directly relevant to the technology-factors result: participants consistently described techno-overload, system complexity and unexplained changes as stressful, but just as consistently attributed the effect of these stressors on their actual output to the presence or absence of organisational and individual resources. One participant explained, "Sometimes I have to work with several systems at the same time, and when all of them require attention, it becomes overwhelming and affects how quickly I can complete my work" (P1), while another linked the practical impact of such overload directly to support: "Introducing technology alone will not solve technostress" without "training, technical support and involvement of employees" (P7). A third participant connected coping ability to outcome irrespective of system complexity: employees who had received adequate training and could rely on IT support described themselves as able to "work through" difficult systems without a loss of output, whereas those without such support described falling behind on targets during system changes. These accounts are consistent with the regression finding that technology factors alone did not significantly predict productivity once organisational and individual response factors were included in the same model: participants' own accounts suggest that it is the presence or absence of resources, not the technology demand itself, that determines whether technostress translates into reduced output.

Table 3 presents a joint display integrating the quantitative results with the corresponding qualitative evidence for each of the three primary factors.

Table 1: Demographic profile of respondents ($N = 368$).

Characteristic	Category	n	%
Gender	Male	192	52.2
	Female	176	47.8
Age	18–25 years	121	32.9
	26–35 years	168	45.7
	36 years and above	79	21.4
Education level	Diploma	84	22.8
	Bachelor's degree	215	58.4
	Postgraduate	69	18.8
Employment experience	Under 2 years	142	38.6
	2–5 years	146	39.7
	Over 5 years	80	21.7

Table 2: Multiple regression of primary technostress factors on employee productivity.

Predictor	B	SE	β	t	p
(Constant)	3.010	0.221	—	13.62	< .001
Technology factors	-0.043	0.050	-0.046	-0.861	.390
Organisational factors	0.129	0.050	0.137	2.585	.010
Individual response factors	0.158	0.049	0.172	3.240	.001

Note. $R = .212$, $R^2 = .045$, adjusted $R^2 = .037$; $F(3, 364) = 5.685$, $p = .001$. Dependent variable: employee productivity.

Table 3: Joint display: quantitative results and qualitative evidence by primary factor.

Primary factor	Quantitative result	Qualitative evidence	Interpretation
Technology factors	$\beta = -0.046$, $p = .390$ (not significant)	Overload and unexplained system changes described as stressful (P1); impact on output linked to support, not the technology itself (P7)	Demand is felt but does not translate into lower productivity once resources are present – consistent with JD-R
Organisational factors	$\beta = 0.137$, $p = .010$ (significant)	Training, technical support and involvement described as decisive for maintaining output	Organisational resources buffer technology demands and independently support productivity
Individual response factors	$\beta = 0.172$, $p = .001$ (significant)	Employees with stronger coping ability described sustaining output through system changes	Individual coping capacity determines whether demands are converted into reduced performance

Table 4: Bivariate correlations among study variables.

Variable	1	2	3	4
1. Technology factors	—			
2. Organisational factors	.284**	—		
3. Individual response factors	.213**	.341**	—	
4. Employee productivity	.046	.187**	.201**	—

Note. $N = 368$. ** $p < .01$ (two-tailed). Employee productivity was not significantly correlated with technology factors ($p = .378$).

Table 5: Summary of hypothesis testing.

Hypothesis	Statement	Result	Decision
H01	Primary technostress factors jointly have no significant effect on employee productivity	$F(3, 364) = 5.685$, $p = .001$	Rejected
H1a	Technology factors have a significant effect on employee productivity	$\beta = -0.046$, $p = .390$	Not supported
H1b	Organisational factors have a significant effect on employee productivity	$\beta = 0.137$, $p = .010$	Supported
H1c	Individual response factors have a significant effect on employee productivity	$\beta = 0.172$, $p = .001$	Supported

4.5 Discussion

This study examined the joint and relative effects of technology, organisational and individual response factors on employee productivity in Kenya's AI-integrated BPO sector. Three findings merit discussion. First, the three factors jointly and significantly predicted productivity, but explained only 4.5% of its variance. This modest explanatory power is consistent with prior technostress research, which typically finds that technostress factors are significant but far from the only, or even the primary, determinants of workplace performance (Whelan et al., 2022); remuneration, motivation, leadership quality, job security and working conditions plausibly account for a larger share of the variance and were outside the scope of this study's productivity model. The result should therefore be read as evidence that primary technostress factors matter, not that they are the dominant influence on productivity.

Second, and central to this paper, technology factors alone were not a statistically significant predictor of productivity once organisational and individual response factors were held constant, whereas both latter were significant. This pattern is well explained by the Job Demands-Resources model: technology overload, complexity and uncertainty function as job demands, but their translation into reduced performance is contingent on the resources available to offset them (Bakker and Demerouti, 2007; Bakker et al., 2023). Where organisational support (training, leadership, realistic workload, IT helpdesks) and individual coping capacity are present, the JD-R model predicts that demands are absorbed rather than converted into strain and lost output – precisely the pattern observed here, and precisely the explanation participants themselves offered in interviews. The finding also qualifies a straightforward Task-Technology Fit account: TTF correctly identifies technology-task mismatch as a source of strain, but the present results suggest that, at the level of productivity outcomes, that strain is moderated by organisational and individual resources to the point where the technology variable's direct effect becomes statistically indistinguishable from zero. TTF: technology fit may still matter for the experience of stress even where its direct link to productivity is masked by resource effects.

Third, the qualitative evidence adds a mechanism that the regression coefficients alone cannot supply. Participants did not describe technology demands as unimportant; they described them as manageable, or not, depending on training, technical support and involvement in how systems were introduced. This is consistent with international evidence that organisational support attenuates the effects of technostress (Kaltenegger et al., 2024; Saleem and

Malik, 2023) and extends that evidence to an East African, AI-integrated BPO context that has received little previous empirical attention (Kleibert and Mann, 2020; Dutta and Mishra, 2024).

Practical implications

For BPO managers, the practical implication is that technology-centred interventions – simplifying interfaces, reducing the frequency of system changes – are unlikely, on their own, to protect productivity if organisational and individual resources are neglected. Investment in structured training, realistic workload expectations, accessible IT support and coping-skills development is likely to yield a larger productivity return than technology redesign alone, a conclusion consistent with the JD-R model's resource-based logic and with the qualitative accounts collected in this study.

Theoretical implications

The study contributes to the technostress literature by testing technology, organisational and individual factors jointly rather than in isolation, in a developing-country, AI-integrated BPO setting that has been under-represented in prior research. It supports the JD-R model's prediction that resources can offset the productivity effects of technology demands, and it illustrates how TTF and JD-R can be combined – TTF explaining the source of strain, JD-R explaining whether that strain translates into reduced performance – to give a fuller account of technostress outcomes than either theory offers alone.

Comparison with prior evidence

The finding that technology factors alone were not a significant predictor of productivity contrasts with several earlier studies that report significant direct technology-productivity associations (Tarafdar et al., 2007; Ayyagari, 2012), but is consistent with studies that, like the present one, model technology factors jointly with organisational or individual variables (Saleem and Malik, 2023; Kaltenecker et al., 2024). This suggests that the discrepancy across the literature may be attributable less to differences in context than to differences in model specification: studies that test technology factors in isolation are, almost by construction, more likely to find them significant, because they cannot separate a technology effect from the resource effects with which it is correlated. The present study's joint specification, and its qualitative corroboration, offer a stronger basis for concluding that, in this BPO context specifically, technology demands are absorbed by organisational and individual resources rather than acting as an independent, unmitigated drag on productivity.

Boundary conditions

The finding should not be read as evidence that technology factors are irrelevant to employee well-being. Even where the resource-buffering account holds for productivity, technology factors may still significantly predict other outcomes not measured here, such as emotional exhaustion, turnover intention or job satisfaction, and qualitative participants clearly experienced technology overload as stressful even when their output was maintained. The appropriate conclusion is therefore that technology factors are a demand that, in the presence of adequate organizational and individual resources, does not translate into reduced productivity in this sample – not that the demand itself is absent or unimportant. This distinction has direct implications for how BPO managers should interpret productivity data: stable output figures during periods of rapid technology change do not necessarily indicate that employees are unaffected by that change, and may instead indicate that existing resources are, for now, sufficient to absorb it.

Implications for AI governance in BPO organisations

The finding that organisational resources, rather than technology characteristics per se, predict productivity has implications for how BPO firms govern AI adoption. Where AI-enabled systems are introduced primarily as a technology project – procurement, configuration and rollout – without a parallel investment in training, workload recalibration and support infrastructure, this study's results suggest that any productivity gains from the technology itself may be offset, or at least not enhanced, by the technostress the same technology introduces. Conversely, firms that treat AI adoption as a socio-technical change requiring organisational investment alongside the technical one are, on evidence, better positioned to protect productivity even as technology demands increase. This is consistent with recommendations elsewhere in the technostress literature that AI-related change management should be paired with explicit organizational-support commitments rather than treated as a purely technical rollout (Whelan et al., 2022; Nastjuk et al., 2024).

Contribution to theory

Empirically, the study extends Task-Technology Fit and Job Demands-Resources research, both developed and mostly tested in higher-income economies, to a developing-country, AI-integrated BPO setting, and provides joint-model evidence, rather than single-factor evidence, of how technology, organizational and individual factors interact to shape productivity. Methodologically, it demonstrates the value of pairing a joint regression specification with thematic qualitative evidence: the regression result alone (a non-significant technology coefficient) could be misread as evidence that technology demands do not matter; the qualitative evidence clarifies that they do matter to employees' experience, but that their productivity effect is contingent on resources, a distinction with direct consequences for how the finding should be acted on by practitioners.

Limitations of the present evidence base

Two caveats temper the strength of these implications. First, because productivity was self-reported, the possibility that respondents' perceptions of their own output were colored by their general attitude toward the organization or toward technology cannot be fully excluded, notwithstanding the Harman test reported in Section 4.1. Second, cross-sectional design means that the direction of the relationship between resources and productivity cannot be established with certainty: it remains possible, for instance, that more productive employees are simply more likely to be given training and support, rather than training and support causing higher productivity. These caveats are addressed further, together with recommendations for future research, in Section 5.

Synthesis

Read as a whole, the results support a resource-centred rather than a technology-centered account of technostress and productivity in this setting: technology demands are real and are experienced as stressful, but their translation into lower productivity is contingent on, and in this sample was substantially offset by, organisational and individual resources. This synthesis is consistent with, and extends, the Job Demands-Resources model's core proposition to a developing-country, AI-integrated BPO context in which that proposition had not previously been tested, and it offers BPO managers a clear, evidence-based basis for prioritizing resource-side investment over technology-side redesign alone when seeking to protect productivity under continuing AI-driven digitalisation.

Directions suggested by the findings for organisational practice

Three concrete practices follow directly from the pattern of results. First, BPO firms introducing new or updated AI-enabled systems should pair the rollout with structured training delivered before, not only after, go-live, since participants linked the absence of prior training directly to lost output during transitions. Second, IT helpdesk capacity should be scaled to anticipated demand during system changes specifically, rather than held constant year-round, given that participants described the after-hours and peak-period availability of support as decisive for whether a technical problem became a productivity problem. Third, because individual coping capacity varied more across respondents than organizational support did, firms may obtain additional productivity protection from targeted coping-skills training for employees who report lower baseline confidence with new systems, rather than from uniform, one-size-fits-all change-management communication alone.

5 Conclusion

This study examined how technology, organisational and individual response factors relate to employee productivity among 368 BPO employees in Kenya, using a sequential explanatory mixed-methods design. The three factors jointly predicted productivity, but only organisational and individual response factors were significant predictors individually; technology factors alone were not. Qualitative evidence indicated that this pattern reflects the buffering role of organizational support and individual coping capacity, consistent with the Job Demands-Resources model. BPO organizations seeking to protect productivity under continuing AI-driven digitalization should therefore prioritize organizational and individual-level interventions – training, realistic workload expectations, IT support, and coping-skills development – alongside, rather than instead of, technology design improvements.

The study has limitations that qualify these conclusions. The cross-sectional quantitative design limits causal inference, and the modest explanatory power of the model ($R^2 = .045$) indicates that other, unmeasured determinants of productivity were not captured. The sample was drawn from BPO providers in Nairobi and may not generalise to other cities, sectors, or countries. Self-reported productivity measures are also subject to common method variance, although Harman's test suggested this was not a major concern in the present data. Future research should test the technology, organizational and individual response factors longitudinally, incorporate objective productivity measures where available, and examine whether the buffering effect of organisational and individual resources observed here generalises to other AI-integrated service sectors in developing economies.

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