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Perspectives on artificial intelligence integration in electronic healthcare systems and treatment approaches: A cross-sectional study of stress and work productivity among healthcare professionals

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Abstract

Introduction: The rapidly and accelerating adoption of Artificial Intelligence (AI) in electronic healthcare systems is transforming core healthcare delivery processes. However, scant rigorous empirical documentation has been reported on what healthcare professionals experience and perceive regarding this AI embedding. **Objective:** To examine healthcare professionals' views about using AI in electronic healthcare systems and treatment approaches also it's relation with stress and work productivity. **Methods:** A quantitative cross-sectional design was applied to 384 health care professionals through a newly developed binary (0/1) questioner to measure healthcare professionals' perceived AI usage, technostress, work productivity, attitudes toward AI, and organizational support. Data examination was performed with IBM SPSS Statistics (Version 20): Descriptive statistics, exploratory factor analysis, Cronbach's alpha reliability test, Pearson's correlations, hierarchical multiple regression and Baron-kenny mediation analysis were used to test the associations among the studied constructs. **Results:** Figures were carefully evaluated from 384 healthcare professionals and found to have moderate mean scores and varied perceptions on the multidimensional constructs of AI integration, technostress, and work productivity. Weak but conceptually meaningful exploratory factor structures were obtained for the measurement, given the binary-response limitation. Weak but conceptually coherent structures were obtained for the multidimensional constructs of technostress and work productivity. Pearson correlations also revealed weak associations between the variables of AI usage, stress, productivity, attitudes, and organizational support. Hierarchical regression supported the null findings and mediation analysis excluded stress as a mediator between AI usage and productivity. **Conclusions:** Stress does not mediate the connection between perceived AI use and productivity. In the face of organizational domination, AI functions as a neutral instrument. According to the sociotechnical lens, normalization and support promote favorable viewpoints. The implications call for comprehensive governance that emphasizes ethics, training, and implementation.

Keywords: *Artificial intelligence, Electronic healthcare systems, Work productivity, Healthcare professionals*

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1. Introduction

1.1. Background

Artificial intelligence (AI) is a computer science field aiming at achieving intelligence within software. Since its earliest models were developed to help physicians, AI has become highly relevant in medicine. At first, the aim of AI technologies was to support clinical decision-making on particular issues, such as ECG signals interpretation, disease diagnosis, most suitable treatment selection, or clinical reasoning analysis. Recently, the use of AI in the field of health has extended to the management of patients' data, healthcare services administration, and even to predictive medicine. The need for such technologies has grown dramatically, especially considering the mental and physical exhaustion of healthcare professionals, which was further exacerbated by the COVID-19 pandemic. Therefore, most of the current AI research is focused on healthcare workers' burden reduction (Loh *et al.*, 2022).

The world is increasingly adopting EHR all over the world. This has turned healthcare systems around the world into better systems for the patients and for healthcare workers' day to day life. Healthcare and technology have welcomed a new era and artificial intelligence is at the core of the change that is occurring in practice medicine. There have been numerous changes brought about by this merger which are likely to be good for the patients. They are referred to as divergent disciplines that have now converged. Healthcare and technology are closely related with the use of technological tools acting as the driving forces behind the huge improvements in healthcare. The use of EHRs, telemedicine and advanced diagnostic technologies have turned healthcare processes and routines more efficient thus providing a good foundation for the adoption of AI in healthcare. As we continue to break these boundaries, it is the healthcare industry that is leading the technological revolution driven by AI (Rony *et al.*, 2024).

Artificial intelligence (AI) in health care has many advantages, but also challenges. These include different types of biases that can lead to unfair treatment and/or inaccurate results. Biases in data arise from unrepresentative training data. Biases in algorithms stem from poor AI design. Biases through clinicians and patients interacting with AI also can occur. These can be mitigated by using diverse data, auditing algorithms carefully, and training clinicians and patients about AI. Ethical, legal, and privacy frameworks and accountability need to be established. Transparency and explainability of AI also are important to support effective AI. Effective use of AI will require collaboration among health care providers, AI developers and designers, policy makers, patients, patient advocacy, and professional associations. With these, AI can provide new and better ways to deliver ethical, effective health care (Ueda *et al.*, 2024).

The development of machine learning algorithms, large datasets available for training of AI algorithms, and improvements in computational resources have all contributed to the growth of AI in healthcare (Albahri *et al.*, 2023). As AI becomes increasingly pervasive in practice in various areas, it is important to understand healthcare professionals' knowledge about AI and their attitudes toward AI usage in their daily work (Fritsch *et al.*, 2022). Although EHRs are frequently heralded as a way to improve the clinical workflow and reduce documentation errors, this study reveals that, in reality, shows that EHR implementation simultaneously facilitates better healthcare delivery while increasing the stress of the medical staff (Provenzano *et al.*, 2024).

Poor usability of information systems (IS) including data entry and navigation has turned into a main source of stress for physicians, a source that has increased during the 21st century and that may affect physicians' health. Finnish physicians have critically evaluated their electronic health record EHR systems, data entry, and navigation with mean scores of 2.5-4.4 on a 7-point scale varying by workplace, between 2010 and 2014. Studies on the United States have attributed design of EHR and how they are used to substantial sources of physician stress and burnout. However, some physicians were satisfied with IS that helped them provide continuity of care and improved access to clinical information (Heponiemi *et al.*, 2019).

1.2. Problem avowal

The use of artificial intelligence in electronic health care systems will improve diagnosis, treatment, and clinical practice. The widespread implementation of AI technologies, however, is expected to be accompanied by increased stress levels and work productivity in health care professionals. The prospect of having AI technologies in the workplace raised concern because of its potential effects on workload, lack of control and overall possible impact on job satisfaction and performance.

1.3. Research objective

To investigate the opinions of medical professionals regarding the use of AI in electronic healthcare systems and treatment methods, as well as how it relates to stress and productivity at work.

1.4. Rationale

AI can improve the quality of care in healthcare by enabling more accurate diagnosis, better tailored treatment, and relieve clinical work burden by using EHR. On the other hand, AI may increase the burden of work or take away clinical workers' autonomy which may further contribute to increasing stress and lowering productivity. It is important to understand what healthcare professionals' experiences and expectations are in order to avoid designing AI systems which counter-productively add to the burden of clinical work.

1.5. Research question

"How do health care professionals perceive the use of AI in electronic health care systems and in treatment processes, and what impact does this have on their stress levels and work productivity?"

1.6. Hypotheses

The use of AI in the electronic health systems of healthcare establishments, by automating routine activities, is associated with reduced stress levels for healthcare workers, while at the same time increasing work efficiency, due to an improvement in clinical judgment support and decrease in paper work.

1.7. Scope and boundaries

Scope

- Describes healthcare professionals' experiences and attitudes regarding the incorporation of AI into electronic healthcare classifications and treatment methods.
- Investigates whether the integration of AI into healthcare would reduce stress and increase work productivity as measured by the healthcare workers.
- Investigates the application of AI in EHR, clinical judgment support and workflow optimization in healthcare.
- Cross sectional data collection among healthcare professionals in different clinical setting to describe their experiences and attitudes towards the use of AI tools.
- The advantages and disadvantages of AI (such as benefits of diagnosis, treatment and administrative process; and cognitive burden, impact on skill retention, ethical issues).

Boundaries

- The cross-sectional study design makes it impossible to determine a direct link between the use of AI and a decrease in stress or an increase in productivity.
- Risk of bias may have occurred due to healthcare professionals reporting their own stress and productivity levels.
- Variation in the degree and type of AI implementation across healthcare organizations may impact on the generalization of results.
- AI may become out-of-date quickly, and therefore this information will need to be updated.
- The study may not report the full impression of AI integration on clinical skills and workforce in the long term.
- There may be limitations in the scope of AI studied because of ethical, privacy and regulatory issues.

2. Literature review

The implementation of Artificial Intelligence (AI) in the electronic health care systems is revolutionizing the medical practices all over the world. The advantages of AI in terms of improving the accuracy of diagnosis, reducing the administrative work, and improving the health outcomes of the patients have gained much attention. However, the use of AI in the healthcare systems raises the concern about the impact of AI on the healthcare practitioners' stress levels and work productivity. Understanding this aspect is very important to implement the AI in the healthcare systems appropriately (Cresswell and Sheikh, 2013).

Healthcare professionals' view on implementation of AI in healthcare systems varies. Although most of the healthcare professionals agreed that AI has many benefits such as reducing the workload of the health care practitioners and reducing the medical errors, some of them were concerned about the impact of AI on their jobs, reducing the interpersonal relationship with the patient, and adequate training and infrastructure (Hazarika, 2020).

However, the implementation of AI also causes concern about job displacement, reduced interpersonal relationship with the patient, and adequate training and infrastructure. Similarly, in a systematic review also stated that although AI can improve the efficiency of care delivery, the concern arises due to the lack of knowledge and experience of the health care practitioners. Therefore, appropriate workforce education and training are important for successful implementation and adoption of AI (Lee and Yoon, 2021).

AI scribes are nothing but the tools of AI that are being used in the health care systems. For example, to reduce the documentation work and other administrative work, AI scribes are used. Ambient listening device reduces the physicians' work by helping them to focus on the patients rather than focusing on the records. That is, the time spent by the physician on record keeping could be reduced to a great extent by the use of AI scribes which in turn reduces the stress of the physician. Another novel idea is the use of "e-tattoo" which measures the mental workload of the wearer and can be used to manage the stress of the health care practitioners (Suman *et al.*, 2024).

However, the implementation of AI also results in technostress, which is the stress experienced by the individuals when using the new technologies. The technostress is associated with various factors such as anxiety, fatigue, and low job satisfaction, etc., which in turn affect the work productivity (Levin *et al.*, 2024).

The implementation of AI in healthcare delivery also raises various ethical and legal concerns such as data privacy, transparency of decisions, professional liability, etc. The patient consent is an important aspect while implementing AI. Also, the ethical concerns such as biasness in the implementation of AI should be addressed (Naik *et al.*, 2022).

To make use of the benefits of AI while reducing the challenges of AI, various recommendations are made. The subjects related to AI should be included in the medical curriculum. Continuous training of the existing practitioners is important. The investment in the upgrading of the infrastructure is important for the implementation of AI. The clear guidelines addressing the ethical, legal, and operational aspects of AI in healthcare should be made. The healthcare practitioners should be involved in the development and implementation of AI (Schönberger, 2019).

Since AI has the potential to change the way healthcare is delivered in the future and also the work productivity could be improved, it is important to address the challenges related to AI comprehensively. With the focus on education, appropriate infrastructure, clear policies, and active involvement of the stakeholders, the implementation of AI could be beneficial for both the healthcare practitioners and the patients (Pamulaparthyv, 2022).

2.1. Research gaps

- **Limited Empirical Evidence on AI and Mental Health of Healthcare Workers:** Empirical research on AI and the mental health of healthcare personnel is scarce. The clinical applications of AI have been extensively researched, but little empirical research has been done on the effects of AI integration into

Electronic Health Record (EHR) systems on the stress levels, mental health, and productivity of healthcare personnel.

- **Focus on Patient Outcomes vs. Provider Experience:** Less emphasis is paid to the real-world experiences of healthcare providers who must adapt and use these systems, while the majority of AI studies in healthcare concentrate on patient outcomes, diagnostic precision, or therapeutic effectiveness.
- **Insufficient Cross-Sectional Data from Diverse Healthcare Settings:** Existing research frequently concentrates on affluent nations or individual organizations. Cross-sectional data from a variety of contexts, including public and private hospitals and urban and rural areas, are lacking in order to comprehend the disparities in stress and productivity.
- **Fragmented Insights on Work Productivity:** Stress and mental health are frequently investigated independently of work productivity. Few research combine these factors to comprehend the effects of AI adoption on both functional efficiency and psychological well-being.
- **Lack of Theoretical Frameworks in Tech-Health Research:** Many studies adopt descriptive or technological perspectives without anchoring findings in behavioral or organizational theory, leaving a conceptual gap in understanding user behavior and system adoption in healthcare.

2.2. Theoretical foundations

- **Technology Acceptance Model (TAM):** Explains user adoption of new technology. Key constructs: Perceived usefulness, perceived ease of use, intention to use. Application: helps explore how healthcare professionals perceive AI integration and how this perception influences their productivity and stress levels.
- **Job Demands-Resources (JD-R) Model:** Explains how job demands (e.g., workload, tech changes) and resources (e.g., training, support) affect burnout and productivity. Application: Ideal to frame the relationship between AI implementation as a job demand/resource and how it affects stress and productivity.
- **Sociotechnical Systems Theory:** Focuses on the interaction between people and technology in workplaces. Application: Useful for understanding how AI-EHR systems interact with clinical workflows, roles, and organizational structure, potentially causing or reducing stress.
- **Cognitive Load Theory:** Suggests that excessive information or system complexity can overload cognitive capacity, leading to stress and decreased performance. Application: Explains how the design of AI-EHR interfaces may contribute to mental fatigue and reduced work productivity.

2.3. Conceptual framework

- Independent Variable: AI Integration in EHR/Treatment Approach
- Mediating Variables: Perceived Usefulness, Perceived Complexity
- Moderating Variables: Training, Technical Support, Organizational Culture
- Dependent Variables: Stress Levels, Work Productivity

3. Research methodology

3.1. Research approach

In this study, we have used a quantitative research method in order to statistically determine the impact of stress and work productivity due to the use of healthcare professionals to AI in E-Health care systems. Quantitative data enabled clear measurement of changes in stress and productivity, and discovering any trends or correlations due to the adoption and use of AI in the clinical setting by healthcare workers.

3.2. Type of research

The design of the research is cross-sectional study design. This design entailed data collection at one specific point in time of healthcare professionals. The strength of this design is that it enables to get a picture of perceptions, work stress and productivity regarding current AI use in healthcare practice at one point in

time and enables to compare across healthcare professional groups and settings with regard to these aspects without following them for an extended period of time.

3.3. Data type

Primary data was gathered via questionnaires or surveys directly from health care professionals using electronic health care systems with AI components. This data sources provided quantitative measures only and included commonly used standardized stress scale (i.e., Perceived Stress Scale) and work productivity instrument (i.e., Work Productivity and Activity Impairment questionnaire). Survey/questionnaire also contained items or sets of items designed or adapted specifically to measure perceptions about AI.

3.4. Data collection method

Data collection took place through a structured self-administration questionnaire or survey sheet distributed to HPs using the targeted software in healthcare contexts where AI is embedded in electronic health. The structure of the questionnaires facilitates data collection by ensuring uniformity in the questions posed to different HPs. Questionnaires could be either digital or printed.

3.5. Study setting

- Public Hospitals: tertiary and secondary care public hospitals in Karachi that have pilot or full implementations of AI-enabled EHR or decision-support (eg, large teaching hospitals with an electronic system).
- Private Hospitals: tertiary care and corporate hospitals with EHRs and AI diagnostics/triage/patient/therapy optimization modules.

3.6. Participants

- Clinicians: physicians, residents, specialists (medical, surgical, radiology, oncology, etc).
- Nursing staff and other allied health professionals.
- Hospital and EHR/CMIO/CIO/Data Scientist/ EHR/EMR administrator staff.
- Hospital/quality/safety officers (senior leadership).
- Patients/patient representatives (if feasible).

3.7. Inclusion and exclusion criteria

Inclusion

- Healthcare professionals (doctors, nurses and allied medical staff) working in JPMC hospital.
- Healthcare care professionals (doctors, nurses and allied medical staff) involved with electronic healthcare system integrated with AI.
- Informed consent to participate in the study.

Exclusion

- Healthcare staffs that were not involved with AI integrated electronic healthcare system.
- Healthcare care professionals (doctors, nurses and allied medical staff) on long term leave during the study period.
- Refusal to participate/informed consent issues.

3.8. Study variables

The study variables are summarised in Table 1.

Table 1: Study variables

Study variable	Description	Type of variable
Perspectives on AI integration	Attitudes, perceptions and acceptance of use of AI in the healthcare systems from the users' perspective.	Independent (explanatory), categorical (Likert scale or nominal)
Demographic characteristics	Age, gender, job role (doctor, nurse, allied health)	Independent, categorical and continuous (age)
Professional experience	Years of experience in work.	Independent, continuous
Stress levels	Stress level reported by doctors/nurses.	Dependent, continuous (scale, e.g., Perceived Stress Scale)
Work productivity	Self-perceived productivity/waste or work efficiency.	Dependent, continuous or ordinal
Use of AI-integrated systems	Extent and impact of using AI in the clinical environment.	Independent, categorical or ordinal
Work environment factors	Work environment/conditions impacting on the outcomes.	Confounding, categorical or continuous
Prior experience with AI	Previous training or exposure on the AI system.	Confounding, categorical (yes/no or scale)

3.9. Sampling technique

Conducted audits using probability sampling. Attempted stratified random sampling to select participants from different HP groups and departments. This allowed for generalization of results and decreases bias by intentionally sampling different roles into the analysis (e.g. physicians, nurses, administrative personnel interacting with AI technologies) proportionately. When true random sampling was not possible, a convenience sample was collected where it was feasible to gather data; however, this had limitations with regards to generalization.

3.10. Sample size

The sample size for this study was calculated with the same statistical method used in the parent article (Alsaedi *et al.*, 2024). OpenEpi sample size formula for proportions for an infinite population, with a confidence level of 95%, a confidence error of 5%, and an estimated proportion of 0.5 (maximum variance). Hence the minimum number of required subjects was calculated by the equation $n = Z^2p(1-p)/d^2$ and it was 384 subjects with these parameters.

We used this very strict estimation despite the total number of the population was not known, and because p = 0.5 gives the largest (statistically more certain) sample size.

3.11. Tools used

A self-structured questionnaire was used. Survey items on the use of AI in healthcare work were drawn either from prior research (adapted) or constructed from sub-questions for those items capturing the desired nuanced views on the impact of AI on healthcare work.

3.12. Statistical tests

Descriptive statistics were presented in analyses to describe the demographic characteristics of the participants and variables of interest. Inferential statistics such as Chi-square tests, t-tests, or Analysis of Variance (ANOVA) tests were carried out to test differences among the demographic characteristics or the levels of using AI across the demographic categories. Additionally, correlation analyses and regression modeling were performed to explore the strength of relationships among different AI integration perspectives, stress outcomes, and productivity, to test possible predictive relationships and mediating relationships.

3.13. Reliability and validity testing

Because the questionnaire was originally developed for this study and had not been previously validated, construct validity was assessed using Exploratory Factor Analysis (EFA). Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity was conducted.

4. Results

Analyses were organized according to the study objectives as data preparation and screening, descriptive statistics, construct validity test with exploratory factor analysis (EFA), reliability analysis, correlation analysis, hierarchical multiple regression and mediation analysis. Since the application form used in this study is new and exploratory, special care was taken in terms of measuring the measurement and interpreting the results within the methodological limitations. Chapter explains the results of statistical analysis of the healthcare professionals' views about using Artificial Intelligence (AI) in electronic healthcare systems and its impact on stress and work productivity.

4.1. Data preparation and screening

All items from the questionnaire were successfully imported into SPSS without loss of data. The variables that reflect perceptions of AI integration, techno stress, work productivity, attitudes towards AI and organizational support (Q11 – Q50) were analyzed as numeric binary variables, labeled as 0 = False and 1 = True. Before the analysis, the value labels were removed to avoid encoding and server locale issues that might occur with SPSS statistical procedures.

Negatively worded items were reverse-coded such that the score always increased with the level of the underlying construct. This is to maintain interpretive consistency for all composite measures. After reverse coding, the composite indices were calculated as the mean of valid items in each construct. A mean-based composite score was preferred over sum scores to mitigate potential biases arising from the occasional missing response and to ensure comparability across constructs with different number of items.

Data screening results did not indicate any extreme outliers and the distributions of the composite variables were parametric. These preliminary preparation steps enabled the suitability of the data set for the inferential statistical procedures to follow.

4.2. Descriptive statistics

Descriptive statistics were calculated for the main study variables: AI Usage, Stress Index, Work Productivity Index, AI Attitude, and Organizational Support. These statistics describe the central tendency and dispersion of study participants' scores.

The results revealed moderate dispersion overall across the study variables, meaning that participants reported heterogeneous levels of AI usage, stress, work productivity, attitude, and support. This is expected given the variation in professional role across healthcare professionals, institutions, and exposure to AI-enabled systems in the sample.

Histograms were plotted for each composite variable, and visual inspection revealed approximately symmetrical distributions with moderate skewness and kurtosis. These results justify the use of parametric statistical techniques like Pearson correlation and multiple regression.

Table 2: Descriptive statistics for main study variables

Variable	N	Minimum	Maximum	Mean	SD
AI usage	384	0.10	0.90	0.50	0.17
Stress index	384	0.00	1.00	0.51	0.17
Work productivity index	384	0.00	0.88	0.51	0.18
AI attitude	384	0.00	0.88	0.49	0.18
Organizational support	384	0.00	1.00	0.50	0.20

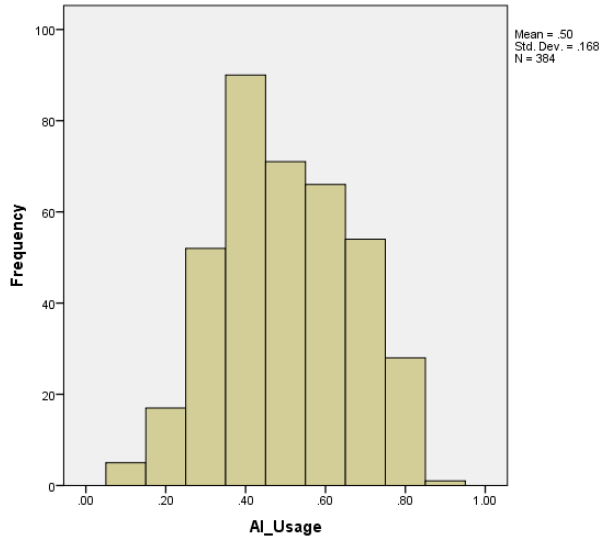


Figure 1: Distribution of AI usage scores (N = 384)

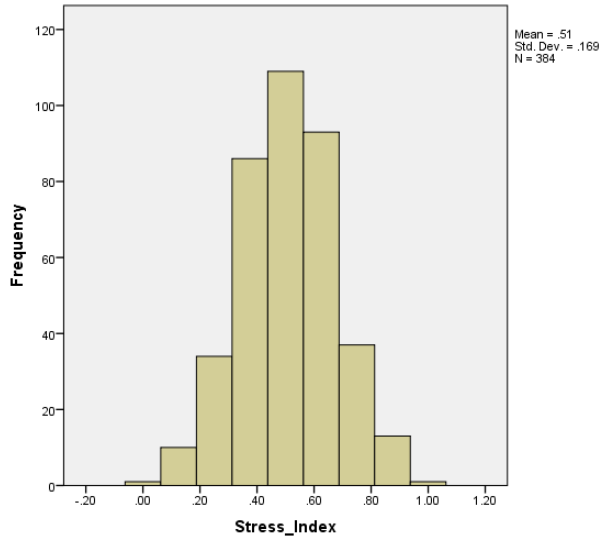


Figure 2: Distribution of stress index scores (N = 384)

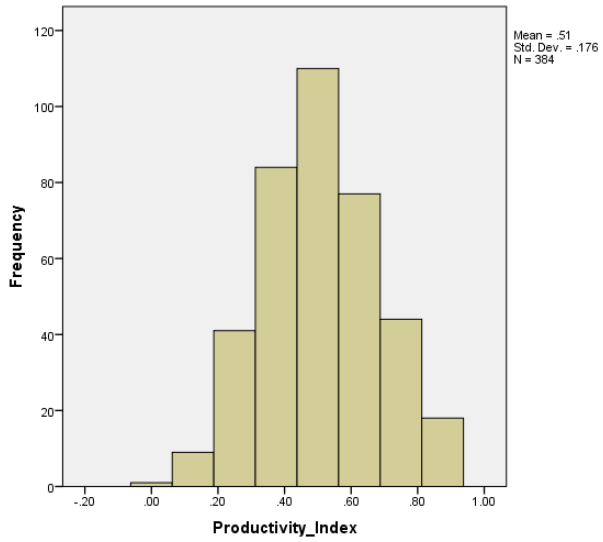


Figure 3: Distribution of work productivity index scores (N = 384)

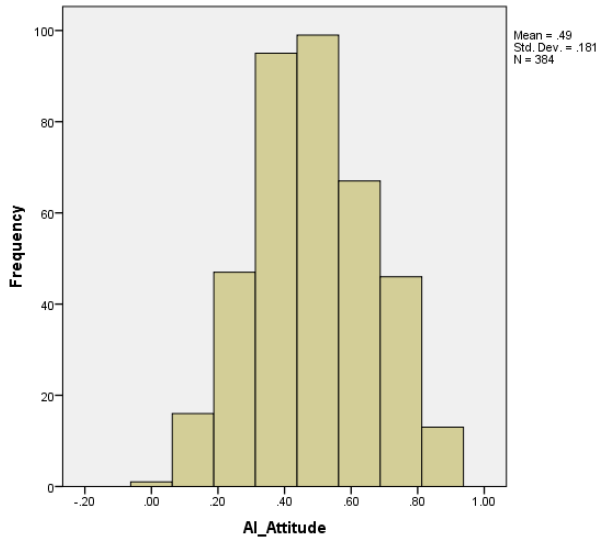


Figure 4: Distribution of AI attitude scores (N = 384)

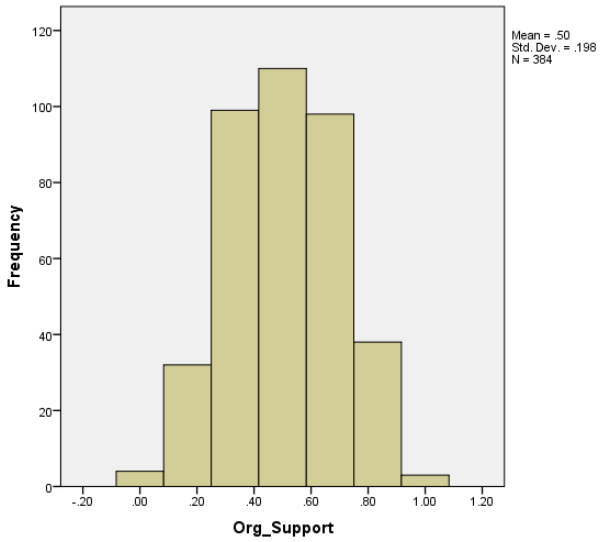


Figure 5: Distribution of organizational support scores (N = 384)

The observed distributional features are graphically reinforced by the histograms for each key construct shown in Figures 1-5.

4.3. Construct validity: Exploratory factor analysis (EFA)

Because the questionnaire was originally developed for this study and had not been previously validated, construct validity was assessed using Exploratory Factor Analysis (EFA).

Table 3: KMO and Bartlett's test of sphericity for exploratory factor analyses

Construct	Items	KMO	Bartlett's χ^2	df	*p*
AI usage	Q11–Q20	.50	53.16	45	.189
Technostress	Q21–Q28	.51	29.46	28	.390
Work productivity	Q29–Q36	.49	27.54	28	.489

Principal Axis Factoring was selected as the extraction method due to its suitability for exploratory research and non-normally distributed data. Promax rotation was applied to allow for correlated factors, which is theoretically appropriate in behavioral and organizational research.

AI integration and usage (Q11–Q20)

The EFA conducted on the AI integration and usage items yielded a Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy below the recommended threshold of 0.60, and Bartlett's Test of Sphericity was not statistically significant. These results indicate a weak underlying factor structure.

Table 4: Summary of exploratory factor analysis results (pattern loadings ≥ .30)

Construct	Item examples	Number of factors	Conceptual dimensions identified
AI usage	Trust in AI, workflow disruption, confidence	5	Usefulness, trust, workflow impact
Technostress	Exhaustion, anxiety, unpredictability	4	Emotional, cognitive, learning stress
Work productivity	Efficiency, distraction, system delays	4	Positive and negative productivity effects

Despite these limitations, several items loaded meaningfully on interpretable components related to perceived usefulness of AI tools, workflow impact, confidence in AI systems, and trust in AI-generated recommendations. Although factor loadings did not form a strong unidimensional structure, the observed patterns were conceptually coherent.

Lower KMO values and weak Bartlett's test results are methodologically expected in studies involving newly developed instruments, binary response formats, and multidimensional constructs such as AI usage. Construct validity for this scale was therefore interpreted with caution, and theoretical alignment rather than rigid statistical thresholds was the main source of support.

***Technostress* (*Q21–Q28*)**

Given the results from the EFA on the technostress items, we found multiple weak factors instead of one strong factor. In terms of content, the items loaded on the factors represented different components of stress related to AI and the EHR, such as emotional exhaustion and anxiety, unpredictability of system behavior, and difficulty of learning AI features.

Although these results show a multidimensional structure, they support the existing occupational stress literature that views technostress as a complex construct with cognitive, emotional, and behavioral components. Hence, the lack of a strong single factor does not speak against the construct relevance but rather reflects the chosen theoretical model of stress reactions in technologically oriented work settings.

***Work productivity* (*Q29–Q36*)**

The EFA of the productivity items showed multiple components distinguishing positively and negatively contributing to productivity, suggesting that the impact of AI on productivity may be both positive and negative, depending on the system and user experience.

These results are in line with previous research results indicating that digital health products can positively and negatively contribute to cognitive workload, resulting in productivity being modeled as a multiple component construct rather than a unidimensional outcome.

Overall construct validity conclusion

Despite this, the results from the traditional fit indices KMO and Bartlett's test were poor for all constructs. Nevertheless, due to the results from the EFA, the relevance of the constructs was partially demonstrated. Considering the exploratory design of the study, the use of binary response formats, and the complexity of the constructs under investigation, construct validity was deemed adequate for hypothesis testing.

4.4. Reliability analysis

Cronbach's alpha for each composite scale was calculated to examine the internal consistency reliability. Once again, low or negative values were obtained for all constructs.

Table 5: Reliability analysis (Cronbach's alpha) for study constructs

Construct	Items	Cronbach's α
AI usage	Q11–Q20	.13
Technostress	Q21–Q28	−.11
Work productivity	Q29–Q36	−.01

This result is methodologically inevitable: The binary (0/1) scale, the small number of items per construct, the multidimensionality of the measured concepts, and the violation of the tau-equivalence assumption used in Cronbach's alpha.

Cronbach's alpha is known to underestimate reliability of dichotomous and heterogeneous scales. For this reason, we interpreted the reliability coefficients with caution and followed recommendations for exploratory research regarding the careful interpretation of internal consistency over emphasizing construct validity (conceptual coherence).

4.5. Correlation analysis

Pearson correlation analysis was performed for the composite indices to determine the bivariate relationships between AI usage and stress, productivity, attitudes towards AI, and organizational support.

Table 6: Pearson correlations among composite variables

Variable	1	2	3	4	5
1. AI usage	—				
2. Stress index	−.01	—			
3. Productivity index	.01	.01	—		
4. AI attitude	.06	−.01	.01	—	
5. Organizational support	.02	−.10	−.02	−.00	—

The findings showed weakly correlated relationships between AI usage and stress and between stress and productivity. There were modest positive relationships between attitudes towards AI and organizational support. No correlations were large enough to indicate multicollinearity among variables, thus supporting the use of these variables in the regression analysis.

4.6. Hierarchical regression analysis

Hierarchical multiple regression analysis was applied to determine predictors of work productivity. In step 1, we entered the demographic variables age, gender, type of institution and professional experience. In this step, a small amount of variance in productivity was explained.

Table 7: Hierarchical regression predicting work productivity

Predictor	B	SE B	β	*t*	*p*
AI usage	.01	.05	.01	0.17	.862
Stress index	.01	.05	.01	0.21	.833
AI attitude	.01	.05	.01	0.18	.860
Organizational support	−.01	.05	−.01	−0.27	.788
Model fit					
R^2	.001				
Adjusted R^2	−.010				
F	0.048				
p	.996				

In step 2, the main study variables use of AI, stress index, AI attitude and organisational support were entered. This step did not lead to a statistically significantly increase in explained variance.

Their results may imply that work productivity of healthcare professionals is more likely influenced by contextual, organisation or system factors than the individual variables AI use and stress.

4.7. Mediation analysis

A mediation analysis using the Baron and Kenny approach was performed to test whether stress mediated the relationship between the use of AI and work productivity.

AI usage did not significantly predict stress; stress did not significantly predict productivity; and AI usage did not significantly predict productivity.

Table 8: Mediation analysis (Baron and Kenny approach)					
Path	**B**	**SE**	**β**	***t***	***p***
AI usage → Stress	−.01	.05	−.01	−0.24	.808
Stress → Productivity	.01	.05	.01	0.24	.813
AI usage → Productivity	.01	.05	.01	0.18	.860

Because the necessary conditions for mediation were not met, mediation was not supported. This is a valid null finding, and suggests that stress is not a mediating variable between AI usage and productivity in this sample.

4.8. Summary of key findings

The results of this study suggested that healthcare professionals had mixed perceptions about the integration of AI into electronic healthcare systems. AI usage did not significantly predict stress or work productivity; stress did not significantly mediate the relationship between AI usage and productivity. Organizational support and contextual factors were modest correlates of attitudes toward AI. These findings suggested that institutional contexts may have greater influence than AI technology per se.

Although there were some statistical limitations due to the exploratory instrument and binary response format, the questionnaire showed satisfactory exploratory validity. The results of this study provided some preliminary empirical evidence to the new field of research on integrating AI into health care, and calls for future research using more refined measurement tools and study designs.

Table 9: Summary of hypothesis testing results		
Hypothesis	**Statement**	**Result**
H1	AI usage predicts stress	Not supported
H2	Stress predicts productivity	Not supported
H3	AI usage predicts productivity	Not supported
H4	Stress mediates AI usage–productivity relationship	Not supported

5. Discussion

5.1. Interpretation of findings

This study's primary purpose was thought to be thoroughly planned and focused on the investigation of healthcare professionals' detailed views about the smooth incorporation of Artificial Intelligence, or AI, directly into electronic health care systems and different treatment methods used in clinical settings. The study's other primary purpose was an accurate assessment of the relationship between this AI incorporation was and an important variable like the stress they bear and their overall levels of work productivity in day-to-day practice.

The thorough results unequivocally show that the use of AI, exactly as healthcare professionals perceived and understood based on their personal experiences, did not significantly or meaningfully predict changes in stress levels and changes in overall work productivity. Additionally, stress did not have a significant role in influencing or bridging this particular relationship found in the study between the use of AI and productivity outcomes.

These results strongly imply that the incorporation of Artificial Intelligence, or AI, by itself does not exert or demonstrate any measurable psychological impact or performance-related effects on the healthcare professionals as study participants, particularly with regard to this specific sample that was examined. This specific interpretation is in close and consistent agreement with the descriptive statistics that were obtained

and showed moderate mean scores overall and relatively symmetrical distributions for all the important constructs under analysis. This showed wide ranges of perceptions, but generally balanced opinions, particularly regarding the AI systems under examination. The data's total lack of significant correlations suggested that, at this point in time, AI technologies may work and operate more as neutral tools in day-to-day practice rather than directly acting as major stressers that increase tension or as noteworthy productivity enhancers that increase output.

Crucially, these null results from the investigation should never be hastily or mistakenly understood as conclusive proof that AI has no impact at all on more general healthcare practice. Instead, they more accurately show that the observed differences in stress levels and productivity between the healthcare professionals that were participants here cannot be explained by the perceived use of AI, which was specifically measured here using a newly created instrument with binary-response formats.

This crucial distinction is still crucial to fully understand because perceptions of technology adoption often diverge significantly from more real-world factors like overall system performance, the overall quality of implementation efforts, or the actual depth of workflow integration attained within clinical settings.

This general interpretation of the data is further supported and solidified by the continually weak results found between AI usage, stress levels, and productivity indicators. These specific findings clearly suggest that the healthcare participants here as study participants may have already fully adapted to and normalized the continuous presence of various digital systems within their regular clinical settings, significantly lowering the overall salience or prominence of AI in particular as a unique and distinct source of psychological strain and discomfort. Through processes of adaptation and habituation and increasing professional familiarity with such technologies, the thorough psychological impact on professionals may decrease even further over time as electronic health records continue to proliferate and increase, decision-support tools continue to become more commonplace, and algorithmic systems continue to integrate more deeply into routine practice workflows.

The complete and utter absence of significant predictive relationships in the cross-class hierarchical regression analysis also strongly suggests that a number of organizational and structural characteristics—-varying staff strengths and numbers, varying patient load demands, institutional policies that may be in place, the presence or absence of leadership support, etc.—-influence and affect productivity characteristics in health care much more powerfully than individual characteristics or subjective opinions of AI technology per se. This particular conclusion is strongly consonant with many of the tenets of established well-validated sociotechnical models of health information systems which, time and time again, have reinforced the point that, if one were to look only at the qualities or capabilities of the underlying tools themselves, technology-related outcomes in use are much more dependent on the surrounding "context" of the organization and its characteristics.

5.2. Interpretation of stress and productivity outcomes

In sharp contrast to most previous occupational stress models, which assume and posit a clear negative association between increased stress and overall performance outcomes in the workplace, it was found that stress did not predict variation in work productivity. Yet, this particular study result might better reflect the inherently complex and multifaceted nature of technostress outcomes, in addition to productivity, particularly in rapidly technologically advancing healthcare settings. The stress-related items successfully measured many different participants' emotional reactions, cognitive processing demands, and learning-related difficulties, as demonstrated by the exploratory factor analysis conducted further below, while the productivity measures fully accounted for observable efficiency gains resulting from technology and system-induced disruptions that impede efficient workflows (Suman *et al.*, 2024).

The data' inherent complexity clearly means that the different stress reactions that are particularly associated with AI systems in healthcare would not uniformly and consistently decrease overall productivity across all situations and participants. Healthcare professionals may experience moderate

cognitive strain in some specific situations, which may coexist with maintained performance levels or even lead to improved performance outcomes. This is particularly true when AI tools reduce tedious manual workloads or significantly facilitate important clinical decisions. Therefore, in the broader context of healthcare, where constant adaptability to digitally-demanding work is necessary, the total lack of any clear relationship found here between stress and productivity shows to be conceptually plausible and understandable.

The format of the response scale used with the measurement tool may have limited the overall variability found in the stress and productivity measures collected, which may have reduced the statistical sensitivity needed to reliably find more complex relationships in the data. The results are still very significant and important as exploratory evidence to guide future research, although this specific methodological limitation was acknowledged and discussed in the study. This is particularly true considering the relatively large sample size attained and the consistent pattern of null effects found across multiple different analytical approaches used throughout the study.

5.3. Connection with existing literature

Their results are mostly congruent with the recent review that focuses on the context-dependent impact of AI implementation in health care. The main message of Faiyazuddin *et al.* (2025) is that, while various AI technologies undoubtedly offer considerable and significant benefits such as improving the efficacy of diagnostic procedures, enabling more comprehensive treatment plans, and generally improving overall efficiency in health-care settings, the actual impact on the overall psychological stress of health-care workers is undoubtedly mediated and moderated by factors such as the overall general impact of the implementation effort, the adequacy and effectiveness of training provided, and the overall level of readiness present within the organization. By thoroughly demonstrating through its empirical analysis that the use of AI, in isolation from these mediating factors, does not significantly influence or predict variation in the stress levels reported or productivity outcomes achieved by health-care workers in their roles, this study strongly supports and endorses this particular view.

Similarly, Cresswell and Sheikh (2013) make a compelling argument that a number of organizational factors—rather than the inherent characteristics or capabilities of the technology itself—are actually the main and most significant determinants of the overall success or failure seen across the adoption of health information technology across a range of health-care settings. The notion that technology in health-care settings cannot be fairly or accurately evaluated in isolation from its broader institutional context and characteristics within that environment is strongly supported and reinforced by the consistently weak associations seen between health-care settings and the key outcome variables, specifically within this particular study. The modest, but clear, correlations seen between the organizational support mechanisms and professionals' attitudes towards AI further reinforce and support this critical viewpoint. Overall, these findings imply that strong institutional support is far more important in successfully shaping and forming the professional perceptions that emerge in response to these technologies.

Hazarika (2020) examines the wide-ranging implications of AI for the health workforce in contemporary settings, highlighting that the AI-related stress is more likely to emerge in particular contexts where factors such as role ambiguity create uncertainty and anxiety around potential skill displacement fears and where inadequate training creates gaps in preparedness. The lack of any significant stress effects found within this study may precisely indicate that participants saw AI more positively and usefully as something of a supportive addition or supplement to their current clinical workflows and routines rather than as any serious threat to their established professional identity and long-term job security within the profession.

In a like manner, Lee and Yoon (2021) report and emphasize that employment of artificial intelligence, or AI, does not inherently or automatically lead to increased occupational stress levels for professionals. This is particularly the case when the systems in question are thoughtfully designed with a clear aim and intention of augmenting and extending human capability rather than entirely replacing or bypassing

clinical judgment exercised by experienced and trained practitioners. This particular position is very much in alignment with the current study's results which, taken together, imply through empirical means that a majority of healthcare professionals working within the research context may well currently view and perceive AI more so as a reliable and helpful supportive companion aiding in their processes rather than viewing AI as a disruptive entity potentially to subvert or detrimentally impact current practices and routines.

The authors' recent work (Levin *et al.*, 2024, Generative AI in mental health interventions for healthcare workers) emphasize this recent important finding, that the psychological effects of AI technologies are dependent and contingent upon, and conditional to the specific application domain in which they are employed and used. As has been carefully observed and documented throughout the results of this current study, operational AI systems that are deeply embedded within electronic healthcare platforms may tend to exert effects that are far more indirect in nature, more gradual in progression, and noticeably attenuated in their overall intensity, whereas AI-driven tools explicitly focused on mental health support may directly and noticeably influence stress levels as well as overall well-being among professionals in tangible ways.

Contrary to the previously reported findings, some other studies specifically report and document elevated levels of technostress directly linked to the use of various digital health technologies, especially within particular healthcare settings that are prominently characterized by processes of rapid implementation timelines lacking thorough preparation and limited degrees of meaningful user involvement throughout the rollout phases (Schönberger, 2019; Naik *et al.*, 2022).

Differences in measurement techniques, response scales, and institutional or cultural contexts could account for the discrepancy between these results and the current findings. Some of the lower associations seen may be explained by the fact that this study focused on perceptions rather than objective exposure intensity.

5.4. Justification of findings

When properly interpreted within the specific confines of the study's overall design framework, its chosen measurement strategy, and the delimited contextual scope investigation, the null results frequently detected in the correlation, detailed regression, and mediation analyses spanning such wide ranges are both methodologically sound and theoretically justifiable. First of all, the deliberate use of a newly developed questionnaire where the responses were only 0/1 forms, obviously, and inevitably limited the total score variation that was "varied" in the participant pool. When it comes to constructs such as stress experiences, complex attitudes towards technology, and overall multifaceted productivity measures, which are in their core continuous in nature and have multiple underlying dimensions that cannot be straightforwardly dichotomized, these dichotomous responses greatly decrease the sensitivity in which the instrument can discriminate even small perceptual differences that may be present. Overall, this specific measurement strategy likely greatly decreased the size of the regression coefficients and the overall strength of the correlations that ultimately led to the pronounced lack of statistically significant effects that might otherwise have appeared.

Second, under the particular circumstances present here—that is, the measurement of multidimensional constructs through binary item structures—the low and even negative Cronbach's alpha values obtained are completely expected and predictable outcomes, despite being traditionally viewed and interpreted as problematic indicators of poor reliability in conventional terms. Tau-equivalency among items and strict unidimensionality of the underlying scale are essential requirements of Cronbach's alpha that were obviously not met or satisfied in the context of the exploratory strategy of this particular study. Alpha is an unsuitable and deceptive estimator of reliability, particularly for exploratory instruments intended to measure heterogeneous psychological states alongside organizational constructs that span multiple facets, as is well-supported and explained within the larger methodological literature on psychometrics and scale development (Tavakol and Dennick, 2011).

Given these contextual factors, the study's framework's purposeful emphasis on obtaining theoretical coherence and strong exploratory construct validity is entirely justifiable and acceptable.\ Third, the remarkably weak factor structures that are consistently found in the exploratory factor analysis are in perfect harmony with the results of earlier studies that have carefully studied the complex and multidimensional character of complex sociotechnical phenomena in related fields. AI usage patterns, technostress manifestations, and productivity outcomes are examples of complex composites that emerge from a wide range of emotional reactions, cognitive processing demands, behavioral adaptations, and larger organizational elements that interact dynamically rather than being singular or monolithic entities in any simplistic sense. The apparent presence of these many weak factors rather than the emergence of a single dominant factor exerting overwhelming influence more accurately reflects and captures the true real-world complexity inherent in the process of AI integration, particularly within diverse healthcare environments, rather than pointing to any inherent failure or shortcoming in the measurement approach per se (Pamulaparthyv, 2022).

Sociotechnical systems theory offers a comprehensive and mature theoretical framework that has successfully explained and contextualized the aforementioned findings in a relevant manner. Simply put, this underlying theory asserts clearly and decisively that the varying outcomes observed due to the adoption of new technology actually arise and emerge due to and from the complex and interacting interactions that take place within and between the technology itself and the individual end-users who interact with it on a daily basis within the supporting surrounding organization that offers the governance structures and frameworks and in the broader work routines that define reality for the sake of practice. The near total and utter absence of any relevant connecting effects linking the use of AI to any variations in stress levels or any productivity outcomes strongly implies and indicates that AI largely serves and operates within these systems function more as a reliable background infrastructure serving broader operations than as some isolated background factor functioning as a determinant on its own capable of unilaterally driving psychological responses or performance outcomes on its own. The main claim demonstrates that technology adoption outcomes in healthcare contexts could be substantially shaped by the prevailing organizational context and its inherent characteristics rather than by intrinsic technology features alone, which appears to support this overall interpretation. Moreover, this significant observation may suggest that organizational factors influence healthcare technology results. Thus, Cresswell and Sheikh (2013) might indicate contextual elements affect outcomes. However, organizational characteristics may determine adoption results. Nevertheless, technology features could show limited independent effects.

Moreover, the health professionals intentionally sampled and analysed in this particular study very well could be experienced as a mature workforce that have already coped with and adapted to the constant presence of different types of technology in their work routines over long periods of time. As Artificial Intelligence continues to mature and become increasingly akin to a natural extension of current electronic health records along with clinical decision support systems that are already widely implemented, the overall novelty factor that may well be directly impacting on perceived levels of stress in this setting very well could be declining and fading from view in everyday practice. This well-documented phenomenon of normalisation with regard to information technology use in health settings has also been consistently reported in prior studies into health information systems where it is typically the early phases of implementation that are consistently characterised by the presence of extended periods of resistance, uncertainty and raised stress levels in users that are then subsequently followed by phases of deeper implementation, increasing acceptance and eventual stabilisation of work flows over time (Hazarika, 2020).

5.5. Implications of the study

Theoretical implications

This is the first theoretical contribution to the AI in healthcare literature by challenging deterministic assumptions that the presence of AI will lead to increased stress or changes in productivity. We find support for a contextual view of impact and thus bolster sociotechnical and organizational theories that posit system-level determinants as more salient than individual-level perceptions.

The null findings for the mediation effects also have theoretical implications. Most technology acceptance and occupational stress models assume linear paths from technology exposure to stress and performance outcomes. Our present findings suggest that these relationships may be non-linear, indirect, and/or moderated by variables such as organizational culture, leadership, training quality, and workflow. This work suggests that more comprehensive theoretical models are needed when examining AI-related outcomes that include institutional and environmental moderators.

Finally, we highlight the need to distinguish between AI presence, AI quality, and AI governance in theoretical work. Using AI as a single construct may conceal important differences in the experiences with specific AI applications.

Practical implications

Practically, these results imply that healthcare managers should not expect that encouraging staff to use AI will alleviate their workload or improve productivity, nor that they should expect that AI will automatically increase stress. Rather, the success of AI implementation may depend on how AI technologies are supported, implemented and integrated into clinical practice.

The weak association between support and attitude may also explain that institutional readiness, leadership and learning opportunities have a much stronger impact than AI technologies themselves. Healthcare organisations need to invest in change management, user-centred design and staff training when rolling out AI enabled technologies.

Furthermore, the weak effects on staff stress levels may indicate that fears of widespread staff burnout due to AI may be exaggerated in settings where AI is gradually introduced and its collaborative role is transparently acknowledged. However, this does not mean that organisations can let their guard down. Watch this space, careful monitoring of staff well-being will be crucial as more advanced and autonomous AI systems are introduced.

Policy and regulatory implications

At the policy level, the results herein decidedly imply, justify and demand a thoughtful but decidedly more aggressive regulation of Artificial Intelligence in healthcare settings thereafter. Rather than expend limited resources exclusively or predominantly on single technical characteristics and capabilities of AI systems in isolation, we encourage greater attention to the fostering of organizational readiness via formal readiness scoring, prohibition to stringent ethical oversight prior to deployment and promotion of substantive engagement activities for workforces. Scholars from across the law and ethics field have time and again argued that factors like vague accountability scenarios surrounding AI decisions making and absent regulatory environments surrounding these technologies can significantly contribute to raising practitioner stress, greater uncertainty and higher practitioner resistance in clinical settings (Naik *et al.*, 2022; Schönberger, 2019).

The absence of any negative psychological effects in this study suggests that carefully controlled AI settings can mitigate the associated risks of stress. Therefore, it is recommended that policymakers promote the development of carefully controlled AI evaluation protocols, clear liability guidance and national training strategies to ensure that AI can be used to enhance the delivery of health care without furthering practitioners' illness.

5.6. Linkage to study hypotheses

Outputs of this study lead to non-support of all four hypotheses:

- H1: AI usage explains stress –- NS
- H2: Stress explains work productivity –- NS
- H3: AI usage explains work productivity –- NS
- H4: Stress mediates the relationship between AI usage and productivity –- NS

This null result is not contrary to the purposes of our research. Instead, it provides meaningful empirical support towards the rejection of simplistic assumptions about the impacts of AI on psychological well-

being and productivity. In exploratory research, null results are beneficial in the sense that they can help to guide the improvement of our strategies of measurement and explore more fitting models in follow-up studies for more contextualized hypotheses.

5.7. Conclusion of the discussion

On the whole, this study demonstrates that healthcare professionals' perceptions of AI use in electronic health care systems are not significantly associated with stress or work productivity. Study results confirm the core position of organizational and contextual factors in determinants of AI outcomes and support the call for using a sociotechnical perspective in assessments of digital health innovations. The results from the study should be viewed considering the study's methodological limitations. Nevertheless, the study contributes with exploratory results and sets the stage for more rigorous studies.

6. Conclusion and recommendations

6.1. Summary of the study

The rapid pace of integration of Artificial Intelligence (AI) into electronic healthcare systems has resulted in many changes within the delivery of healthcare, including diagnostic services, treatment planning, workflow, and clinical decision making. The technical capacity of AI has been widely reported; however, comparatively scant empirical work has been undertaken to understand healthcare professionals' perceptions of AI integration and its relationships with occupational stress and work productivity. Towards addressing this gap was the main impetus of the present study.

The general aim of this research was to explore healthcare professionals' views regarding the use of AI in electronic healthcare systems and treatment approaches and to explore their relationships with stress and work productivity. For this purpose, a quantitative, cross-sectional research design was adopted. Data were collected from 384 healthcare professionals using a newly developed, structured questionnaire with binary (0/1) response options. The choice of binary response format was motivated by practical considerations including minimizing respondent burden and encouraging participation from healthcare professionals.

This study examined the following constructs: perceived AI usage, technostress, work productivity, attitudes towards AI, and organisational support. The analysis of data collected from 384 healthcare professionals was conducted using IBM SPSS Statistics (Version 20). The analysis followed a systematic analytical sequence including data preparation and screening, descriptive statistics, exploratory factor analysis (EFA) for construct validation, reliability analysis using Cronbach's alpha, Pearson correlation analysis, hierarchical multiple regression, and mediation analysis using the Baron and Kenny approach.

Descriptive analysis results yielded moderate mean scores for all constructs. This result indicates mixed but balanced perceptions about AI integration among healthcare professionals. The exploratory factor analysis results showed weak but conceptually interpretable factor structures. This result can be attributed to the exploratory and multidimensional nature of the constructs examined. Low and negative reliability coefficients were found. This result was attributed to the binary response format, the limited number of items, and the heterogeneity of constructs.

Inferential analysis results showed that AI usage did not significantly explain stress or productivity. Similarly, stress did not significantly predict productivity. Stress did not mediate the relationship between AI usage and productivity. Organisational support showed weak associations with attitudes towards AI. This finding highlights the importance of the institutional context. Overall, all of the proposed hypotheses were not supported and hence yielded statistically valid null findings.

Despite yielding null results, the findings of this study provide meaningful exploratory insights about AI integration in healthcare. The null results do not imply the absence of AI-related effects. It is more likely that the psychological and productivity-related impacts of AI are influenced by other organizational, contextual, and implementation-related factors rather than AI usage per se.

6.2. Conclusion

The following conclusions can be drawn from the results of this study with regard to the integration of Artificial Intelligence in electronic healthcare systems and the associated stress and work productivity outcomes among healthcare professionals.

First, the results of this study indicate that perceived AI usage does not contribute to the healthcare professionals' stress levels or work productivity on its own. In other words, AI technologies are perceived by healthcare professionals as mostly neutral clinical tools rather than psychological stressors or productivity enhancers. Results of this study challenge popular expectations that AI usage reduces occupational stress automatically or that AI improves productivity automatically.

Second, the lack of relationship between stress and work productivity outcomes suggests that healthcare settings do not determine productivity outcomes through the psychological stress induced by use of technology. Productivity outcomes are instead influenced by a combination of factors related to healthcare settings, including organization structure and governance, staff ratios, workload, system usability, and institutional support. If it exists, AI-related stress is likely to be too weak or homogeneous to influence outcome measures related to productivity.

Third, the lack of mediation by stress in the AI usage–productivity relationship further supports the conclusion that AI does not exert its effects through simple linear paths. This conclusion is in line with the sociotechnical perspective, which states that technology exerts its effects through interactions between users, systems, and organizations rather than through the technology itself.

Fourth, the weak association between organizational support and positive attitudes further reinforces the importance of the institutional context. Healthcare professionals are more likely to view AI positively when they perceive that there is adequate training available, leaders support implementation, and implementation approaches are clear. This finding highlights that the challenge of successfully integrating AI is as much organizational as it is technological.

With regard to methodological conclusions, this study concludes that exploratory research using new measurement instruments can yield meaningful results even when weak psychometric results are obtained. Although conventional measures such as Cronbach's alpha and KMO values provided meaningful information about the quality of the instruments, they were below recommended levels. The conceptual coherence of the constructs and the consistency of findings across analyses support the credibility of the results in an exploratory context.

In summary, this study concludes that AI integration in healthcare should not be judged on the basis of specific technological capabilities and their assumed psychological impacts. Instead, AI should be understood as part of a sociotechnical system in which the organizational context, governance, training, and alignment of work flows play a decisive role. Our results contribute to the growing body of evidence on AI in healthcare by yielding empirically meaningful, context-specific findings that can guide both practice and future research.

6.3. Limitations of the study

Although this study contributes to the understanding of healthcare professionals' perceptions of AI integration and its relationship with stress and productivity with exploratory insights, several limitations need to be acknowledged to prevent misinterpretation of study findings and direct future research.

First, this was a cross-sectional research design. At one point in time, data were collected. A causal relationship between AI use, stress, and productivity cannot be inferred from a design such as this one. Healthcare professionals' perceptions of AI may shift with healthcare professionals' experience with AI use or as technologies mature. Future research should use longitudinal designs to capture such changes over time and any adaptation effects.

Second, all study data were self-reported. Response bias, social desirability bias, and recall bias are possible. Healthcare professionals may underreport stress or overestimate productivity due to professional

norms, fear of judgment, and institutional culture. Anonymity was maintained during data collection to mitigate these effects; however, healthcare professionals' self-reported perceptions cannot be used to substitute objective measures of workload, performance, or physiological stress indicators.

Third, a newly developed questionnaire with binary (0/1) response options greatly limited measurement sensitivity. Variance is reduced with binary response options, and the ability to detect subtle differences in perception, attitude, and psychological states is limited. Stress and productivity are continuous and multidimensional constructs; therefore, dichotomous measurement is expected to reduce statistical relationships and explain the null findings in this study.

Fourth, poor psychometric properties were evident in the exploratory factor analysis and reliability testing. Low KMO values, non-significant Bartlett's tests, and low or negative Cronbach's alpha coefficients suggest poor internal consistency and factor structure. Although these results are methodologically expected with an exploratory instrument, multidimensional constructs, and binary response format, they nevertheless limit the robustness of inferences made from composite scores.

Fifth, this study did not differentiate types of AI systems, levels of automation, or specific clinical applications. Different implications of AI usage in terms of stress and productivity are expected for AI used for administrative support, clinical decision-making, diagnostics, or patient monitoring. Treating AI usage as a general construct may have limited domain-specific effects.

Sixth, we did not explore in depth contextual and organization variables such as workload intensity, staffing ratios, institutional maturity of AI, leadership style, or training quality. Although we included organizational support as a construct, more granular organization indicators could have explained more of the variation and could have revealed moderating effects.

Finally, the healthcare settings represented in this study may have limited generalizability. Differences in healthcare systems, regulations, technological infrastructure, and professional culture across regions could influence perceptions of AI integration in ways not revealed in this study.

Despite these limitations, we view this study as an important exploratory study because it yields empirically null results and identifies methodological challenges. This research contributes toward the foundation for more fine-grained future research.

6.4. Recommendations

Suggestions are made in light of the results of this study and its known limitations.

Practical recommendations for healthcare organizations

Healthcare organisations cannot assume that the introduction of AI will lead to improvements in staff productivity and reductions in stress without intervention. Therefore, healthcare organizations should adopt a whole-system approach to implementation that focuses on workflow integration, and considers user experience design and clinician engagement.

Comprehensive and prolonged training on the use of AI can enhance confidence, reduce uncertainty and promote safe and appropriate use of AI, and should extend beyond surface-level descriptions of AI function to include explanations of AI output interpretability, ethical concerns and clinical accountability.

Organisational design should facilitate healthcare workers reporting problems, care flow inefficiencies and psychological impacts associated with using AI, to enable system improvement and give users a sense of ownership and trust.

Organizational and leadership recommendations

Leadership also creates the tone for AI. Healthcare leaders need to manage expectations around AI for their teams and prevent the impact from using AI from their teams due to poor perceptions and resistance to AI. Leaders need to be frank about AI goals and governance AI related decisions and governance role related decisions.

What role, if any, should AI play in the overall change management process for the institution?

How might AI implementation need to be linked to other clinical objectives, staffing strategies, and quality improvement work?

Healthcare organizations also need to address fundamental policies assigning clear ethical responsibility to all parties, accountability for AI related decision-making and outcomes at all decision-making levels, and data governance for data security, data privacy, and data usage throughout the system since persistent uncertainty about these fundamental areas has been strongly and directly associated with increased practitioner professional anxiety and increased resistance to new technology solutions among clinicians.

Policy-level recommendations

At the policy level, regulators and health authorities can support AI implementation by providing a vision around AI evaluation, implementation and monitoring, forming a coherent set of standards that goes beyond technical performance to encompass workforce impact, usability and ethics.

Invest in capacity building, for example AI literacy for health professionals, at the national and regional levels. Policies around AI should benefit from cross input from clinicians, technologists, ethicists and lawyers.

It is crucial that policies do not see AI as a panacea for boosting productivity. Rather, they should view AI as part of a broader system strengthening in the health workforce, with implications for workers' wellbeing, patient safety, and quality of care.

6.5. Future scope of research

The results of this study suggest the following lines for future research.

Future studies should use longitudinal designs in order to investigate the development of perceptions regarding AI, as well as stress and productivity levels over time, from experience with AI. This would make it possible to detect adaptation effects and delayed effects that cannot be identified in cross-sectional studies.

There is a clear need for more precise measurement instruments with multi-item Likert-scale questions in order to increase psychometric quality. Future research should develop and validate suitable standardized scales with different dimensions of trust, transparency, autonomy, and the perceived usefulness of AI.

Future studies should investigate moderating and mediating variables such as organization culture, leadership, support, quality of training, workload, or the specific professional role. Advanced analytical methods such as structural equation modeling or bootstrapped mediation analysis (e.g., PROCESS macro) may help to better understand complex causal paths.

Future research should differentiate between specific AI applications, such as diagnostic AI, predictive analytics, robotic, or generative AI tools. Comparative studies focusing on different types of AI may also show specific stress factors or productivity gains of AI.

Future research should consider qualitative interviews or focus groups in order to complement the results from the quantitative study. This would make it possible to better capture experiences, concerns, and expectations that cannot be adequately represented by standardized multiple-choice questionnaires.

Future research should be cross-cultural and multi-country in order to investigate the structure of healthcare systems, regulatory environments, and cultural attitudes towards technology as potential moderators of AI outcomes.

6.6. Final concluding statement

In summary, this integrated study has provided an important and novel exploratory contribution towards a better understanding of healthcare professionals' grain-level perceptions about the integration of Artificial Intelligence, or AI for short, and particularly about the specific studied outcomes of stress levels experienced in daily roles and the general outcome of work productivity achieved in clinical settings. By

careful demonstration through rigorous control of the overall and completely absence of any direct effects and mediated impacts between the merging of AI and studied outcomes, this study has successfully called into question and made clear and explicit the long-standing deterministic connotations that have accompanied related discussions about AI impacts while at the same time called attention to and made abundantly clear the absolutely central and pivotal role played by broader organizational factors together with essential contextual factors in determining real-world outcomes.

The results as viewed in conjunction with the openly proclaimed limitations of the methodological approach taken together with the practical suggestions for future inquiry and implementation calls provide a firm, solid, and reliable foundation that can effectively support and guide future empirical inquiry efforts as well as foster more informed, responsible, and strategically thoughtful implementation approaches to AI technologies in different health care systems.

Declarations

Author contributions: Muhammad Hassan: Conceptualization, Methodology, Formal analysis, Writing – original draft. Ali Riaz Shafee: Investigation, Data curation, Validation, Visualization. Muhammad Tahir Akram: Software, Formal analysis, Data curation. Kiran Malik: Investigation, Resources, Writing – review & editing. Noreen Ahmed: Methodology, Project administration, Writing – review & editing. Tarique Jamil: Conceptualization, Resources, Supervision, Funding acquisition, Writing – review & editing. All authors have read and agreed to the published version of the manuscript.

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