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Job Crafting and Technological Self-Efficacy as Mitigators of AI-Related Emotional Exhaustion among English Educators

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Abstract

This study has been conducted in a rigorous way to determine the association between emotional fatigue and awareness of artificial intelligence among English teachers, and specifically in relation to moderating factors of job crafting and technological self-efficacy. By applying the snowball sampling technique based on online and professional networks, it was possible to collect data on 388 faculty members in tertiary and secondary institutions and, thus, place the study in the framework of the Job Demands Resources Model and Digital Technology Self-Efficacy framework. Numerical analysis (Structural equation modeling) showed that there existed a strong positive relationship between AI awareness and emotional exhaustion ($\beta = .32$, $p < .001$), thus, validating the usefulness of AI as a job demand in modern educational institutions. However, the job crafting ($\beta = -.24$, $p < .001$) and technological self-efficacy ($\beta = -.41$, $p < .001$) also proved to be significant moderators, although the latter has a significant stronger buffering effect. These findings highlight the fact that teachers with high technological confidence and practice proactive work-re-design in their work are likely to have reduced stress caused by AI. The paper sheds light on a contradictory process according to which AI serves both as a demand and at the same time (depending on the personal psychological and behavioral reaction), as a possible resource. Practical implications then involve having focus on the development of technological self-efficacy and nurturing organizational cultures that are keen in promoting job crafting. The psychological adjustment of educators in the digital transformation era is also one of the key factors to successful AI technologies integration. The future research must utilize longitudinal designs to follow the development of these protective variables during prolonged durations of AI exposure and examine cross cultural differences in educator reactions to technological disruption.

Keywords: Job Demands-Resources Model, Teacher Burnout, Professional Adaptation, Workplace Stress, Educational Technology

Introduction

The use of artificial intelligence has taken a central stage in a wide range of fields of professional activity, and the educational field is no exception since modern literature proves it (Holmes et al., 2023). Within the context of the English language teaching, where the unique ability of human creativity and critical thinking has been the cornerstone of the teaching process, the proliferation of AI, with its high efficiency in composition, automatic content production, and language processing, presents a significant threat to the very existence of the teaching process (U.S. Department of Education, 2023). Although one cannot deny the fact that AI can also be used to supplement teaching plans and service quality in English departments, the accompanying technological supplement also poses some significant substantive issues to the issue of maintenance of the intrinsic value of human expertise in teaching language. The spread of AI platforms, the example of Claude, ChatGPT, Grok, and their peers, has a consequential effect on the teaching of English. These tools are used by educators to simplify a plethora of activities, including the analysis and writing of tricky texts or automating assessment procedures, among other aspects, and rework the boundaries of their professional duties (Holmes et al., 2023). As a result, an increasing number of teachers become sensitive to the slow reorganization of their functions as teachers, facilitators, and assessors due to the power of AI. This has been described as the so-called AI awareness (Chen & Jang, 2019). However, as we admit the growing role of AI technologies in the educational environment, the consequences of AI awareness among educators in their psychological well-being, professional identity, and coping mechanisms have not been adequately examined.

The current research aims at offering an inquiry that is comprehensive and aimed at investigating the relationship between AI awareness and the well-being and pathways of adaptive strategies among high-school teachers and university professors, by merging the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2017) with the Digital Technology Self-Efficacy model (Hughes, 2024) and the concept of Job Crafting. Based on the JD-R paradigm, job demands are suggested to have an effect on the emotional condition of educators, which leads to the emergence of burnout and strain when there is no sufficient provision of resources and psychological alleviation mechanisms (Bakker & Demerouti, 2017).

Job crafting is a potential resource identified under this theoretical architecture and allows educators to actively redesign their professional environment and avert the possible stressors. Job crafting refers to the intentional changes that workers make on their work and even on their interprofessional networks (Wrzesniewski & Dutton, 2001). Such crafting can manifest itself in the context of English education in the form of reframing professional identity, as an adversary, to viewing AI as an ally, or in the form of building new forms of pedagogy that allow an integrated incorporation of AI technologies, without neglecting other distinctively human skills, including emotional intelligence and cultural reflexivity. Regardless of the revolutionizing nature of job crafting, its effectiveness depends on the ability of educators to be confident in their technological skills.

Technological self-efficacy is identified as one of the central individual resources in modern digital ecosystems (Bandura, 1986; Compeau & Higgins, 1995). To educate English teachers on their way through AI implementation, the level of their technological self-efficacy defines the nature of AI in terms of being harmful or the tool of professional development. Teachers who have a strong self-efficacy are better placed to work positively with AI instruments, learning to apply new resources that enhance their teaching skills, and not to harm them.

Research Model and Hypotheses

According to the theoretical framework presented above, our research model is that of a study of the direct impact of AI awareness on emotional exhaustion, and that the impacts of job crafting and technological self-efficacy are also examined as moderators. Our conceptual model is graphically presented in Figure 1 and shows the relationships that are proposed.

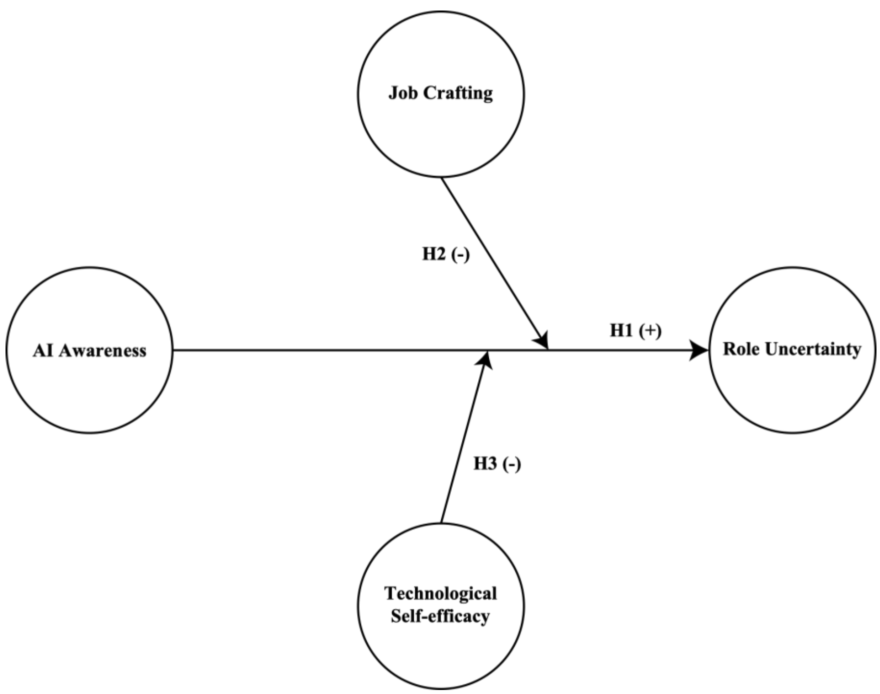

Figure 1: SEQ Figure * ARABIC 1. Direct effect of AI awareness on emotional exhaustion and moderation effects of job crafting and technological self-efficacy

H1: AI awareness positively predicts emotional exhaustion among English educators.

H2: Job crafting weakens the positive relationship between AI awareness and emotional exhaustion.

H3: Technological self-efficacy weakens the positive relationship between AI awareness and emotional exhaustion.

Methodology

This research utilizes a quantitative, cross-sectional survey approach to investigate the hypothesized relationships.

Participant Recruitment Process

The recruitment method was a snowball sampling technique which targeted English teachers in high schools and professors in universities. Professional networks that existed in advance were used in this approach, and in it, the first participants referred other colleagues who met the inclusion criteria. Additionally, the recruitment was also expanded with the use of other online platforms, i.e., LinkedIn, Facebook, and WhatsApp that were applied as professional networks to reach educators in relevant groups and communities, and Prolific provided access to a heterogeneous pool of education professionals willing to take part in research.

Sample Characteristics

The final sample comprised 388 participants with 58% of the sample being high-school teachers and 42% being university professors, hence fulfilling the required inclusion criteria. The demographic analysis has shown that mean age is 31.5 and the mean teaching experience is 9.3 years. The table below (Table 1) shows that gender distribution was 65% female and 35% male.

Table 1: SEQ Table * ARABIC 1
Sample Characteristics and Demographics

Sample Characteristic	Value
Sample Size	388
Education Level	
High School Teachers	58%
University Professors	42%
Demographics	
Average Age	31.5 years
Average Teaching Experience	9.3 years
Gender Distribution	
Female	65%
Male	35%

Data Collection Timeline

It took place over a three-phase timeline of the research. Phase 1 would be a two-week pilot, which would allow streamlining the survey instrument based on the initial responses. Phase 2 was the primary period of data collection that lasted eight weeks and involved a survey recruitment, distribution, and reminder on various platforms. Phase 3 was dedicated to three weeks of the follow-up processes, which included non-response follow-up, intensive data quality audits, and affirmation of the final sample.

Survey Structure and Measures

The questionnaire instrument is structured into four parts. Section A, collects demographic data- Age, gender, teaching experience, education level and type of institution. Section B measures the core constructs through the validated scales: AI Awareness (8 items), Emotional Exhaustion (9 items; Maslach & Jackson, 1981), Job Crafting (15 items; Slemp & Vella-Brodrick, 2013) and Technological Self-Efficacy (17 items; Hughes, 2024). Part C contains some additional questions that demand open-ended answers to issues of AI implementation, technological development requirements, and technology use trends.

Quality Control Measures

There are a number of quality-controlling mechanisms that protect the integrity of data. The checks include attention check items, analysis of response time, pattern detection and duplicate-IP check. The strategies to reduce bias are neutral framing of questions, randomization of the order of item, non-response-bias analysis, and social desirability controls. Compliance with ethics is guaranteed by the IRB approval, informed-consent process, anonymization of the data, and high-level data security measures.

Statistical Analysis Pipeline

The analytical procedure has three stages that are systematic. The initial phase involves data screening, descriptive statistics, assumption test and missing-data analysis. Measures, stage involves confirmatory factor analysis, reliability evaluation, validity evaluation and model-fit evaluation. The structural-model step looks into the testing of the hypothesis, moderating analysis, bootstrap techniques, and assessing the effect-size.

The SPSS 28.0, SmartPLS 4.0, R 4.3.0, and the Survey tool, Qualtrics are the major software used in the study. The total timeline is five months including one month preparation, two months of data collection, a month of analysis and one month of reporting.

Data Analysis

The data-analysis procedure is expressed by the systematic method that consists of eight steps that start with the preliminary data gathering and end with the ultimate academic reporting.

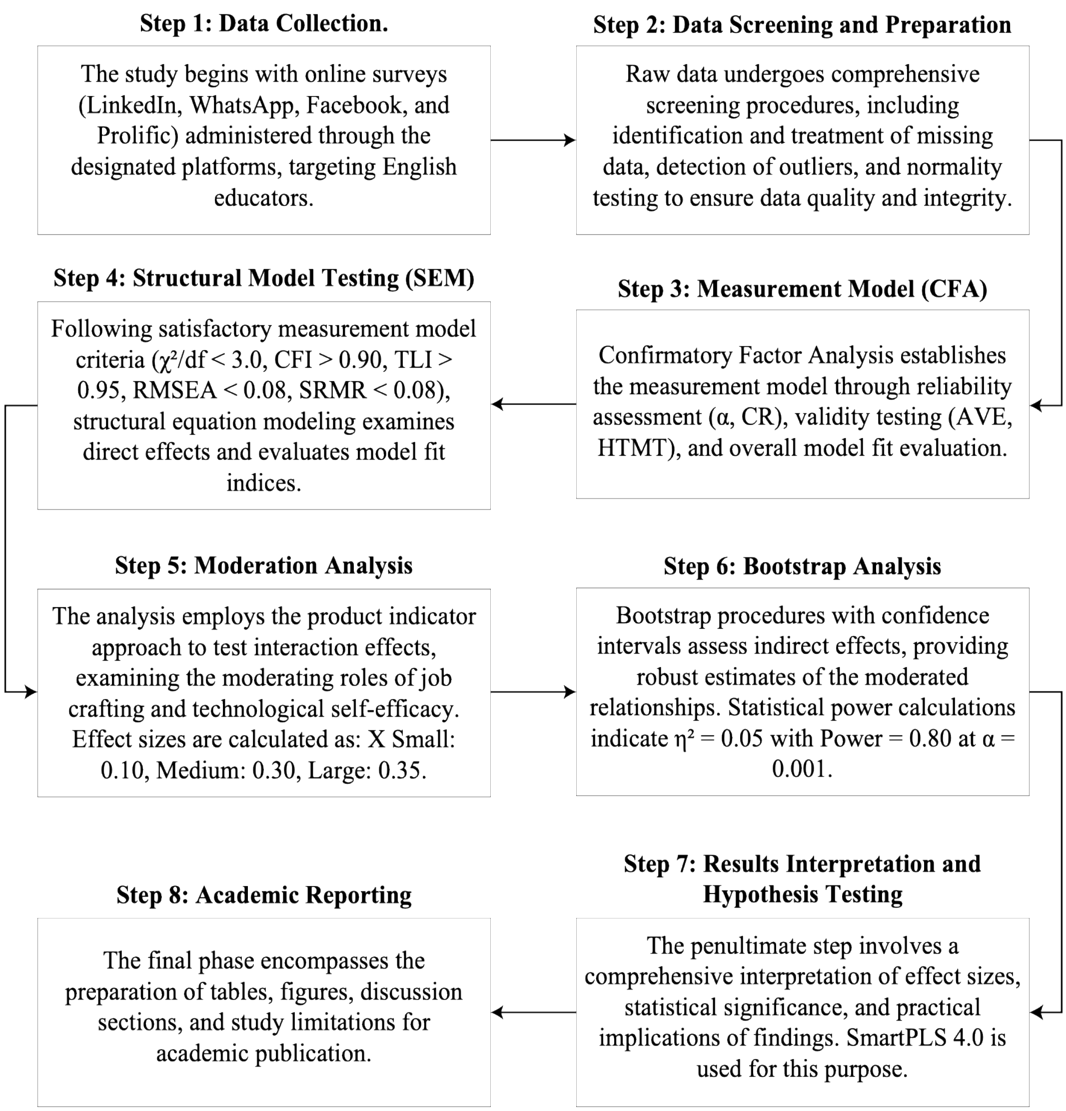

Figure 1: Data analysis flowchart

Results

Measurement Model Assessment

The first measurement model revealed the desired fit indices (Cui, 2025) (Table 2).

Table 1 : Measurement model fit indices

Fit Index	Value	Recommended Threshold	Assessment
χ^2/df	2.34	< 3.0	Good fit
CFI	0.95	> 0.90	Good fit
TLI	0.94	> 0.90	Good fit
RMSEA	0.059	< 0.08	Good fit
SRMR	0.048	< 0.08	Good fit

Nonetheless, a closer look at the factor loadings showed that thirteen of the items in the four constructs (Table 3) are below the suggested percentage of 0.60 (Hair et al., 2017). Namely, two items of AI Awareness (AIA2, AIA7), three items of Emotional Exhaustion (EE3, EE6, EE9), four items of Job Crafting (JC1, JC5, JC8, JC14), and five items of Technological Self-Efficiency (TSE3, TSE6, TSE10, TSE13, TSE16) showed poor factor loading. These were then eliminated and the measurement model was again estimated to allow acceptable convergent validity.

Table 2: Standardized factor loadings for final measurement model

Constructs	Items	Factor Loading	Cronbach's α	CR*	AVE**
AI Awareness	AIA1	0.72	0.87	0.88	0.55
	AIA4	0.81			
	AIA5	0.79			
Emotional Exhaustion	EE1	0.82	0.91	0.92	0.62
	EE4	0.85			
	EE7	0.83			
	EE8	0.79			
Job Crafting	JC2	0.71	0.89	0.90	0.51
	JC4	0.74			
	JC7	0.73			
	JC9	0.75			
	JC11	0.72			
	JC12	0.64			
	JC13	0.71			
	JC15	0.73			
Technological Self-efficacy	TSE1	0.76	0.93	0.94	0.68
	TSE4	0.81			
	TSE5	0.77			
	TSE7	0.74			
	TSE9	0.75			
	TSE11	0.78			
	TSE14	0.79			
	TSE15	0.73			
	TSE17	0.74			

*Composite Reliability;
**Average Variance Extracted

Structural Model and Hypothesis Testing

The hypothesis-testing results are provided in Figure 3**.**

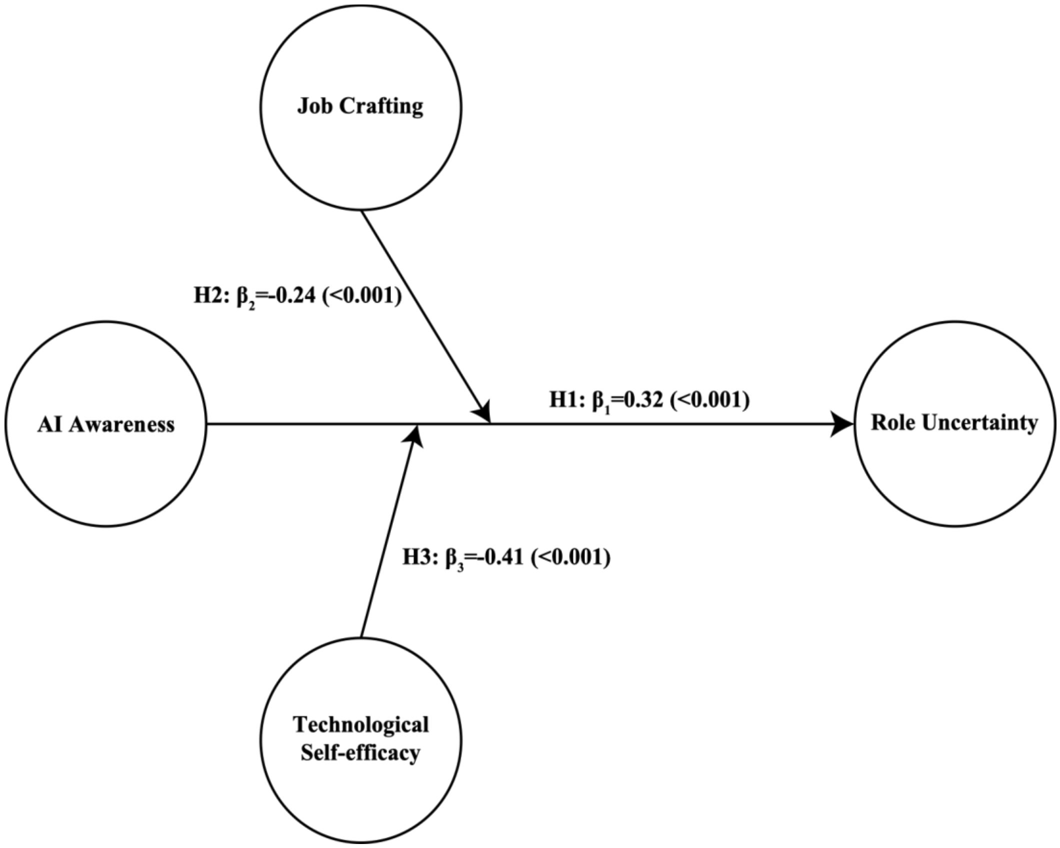

Figure 2: Structural model results and hypothesis testing

Each of the three hypotheses was accepted. Emotional exhaustion was strongly predicted by AI awareness ($\beta = .32$, $p < .001$), which confirmed H1. The relationship between the emotional exhaustion and AI awareness was significantly mediated by both job crafting ($\beta = -.24$, $p < .001$) and technological self-efficacy ($\beta = -.41$, $p < .001$), which supports hypothesis H2 and H3 respectively.

Discussion

The given study may be seen as evidence of the psychological dynamics affecting the relationship between the AI introduction into the educational sectors and the psychological well-being of teachers. The results confirm the two-sidedness of the technological progress in the educational field by showing that awareness of AI is a significant predictor of emotional exhaustion among the English teachers. The given relationship supports the Job Demands - Resources Model (Bakker & Demerouti, 2017). It implies that the increased attention to the AI features increases the level of role confusion and professional insecurity as teachers start doubting their role and duties.

Altering influences of technological self-efficacy and job crafting can give a better idea of how teachers can manage the digital transformation. Job crafting is a key in alleviating the effect of emotional exhaustion as a result of AI. Such an observation implies that the chances of teachers facing the psychological pressure linked to the use of AI tools are lower when they embrace emerging AI technologies by using AI tools in their pursuits and urging their students to engage with AI instead of competing with it.

Technological self-efficacy proves to be a considerable buffer to the adverse effect of AI awareness on emotional exhaustion of educators, which is more prominent than job crafting. The discovery echoes the self-efficacy theory by Bandura (1986) in general and the context of the AI integration in education in particular. Teachers who are more confident about their skills in using technological devices consider AI tools as a helper and not a threat. This view point allows them to enjoy AI tools without letting the same to adversely impact their professional well-being and identity. The greater mitigating role of technological self-efficacy than job crafting shows that internal psychological resources play a stronger protective role than behavioral adaptation, especially in the mitigation of the effect of AI awareness on emotional exhaustion. This difference underlines that any intervention which aims at improving the technological self-efficacy of educators will have more beneficial influences on their well-being than an intervention that operates only with the help of role-tailoring strategies.

These results also indicate that AI awareness cannot be directly related to an effect and cause relationship with emotional exhaustion. Instead, it is the other psychological and behavioral nuances that moderate the relationship.

Limitations and Future Research

Although this research study offers relevant information on the psychological implications of introducing artificial intelligence into the educational setting, there are a few constraints that should be given a close attention. The cross-sectional approach does not allow the inference of causation to be given to other relationships between AI awareness, emotional exhaustion, and the mentioned moderating variables. Additional longitudinal studies are necessary to clarify how these dynamics change over time, especially when educators get used to AI tools and when AI tools are improving in their capabilities. Such studies can show whether the positive effects of job crafting and technological self-efficacy increase or dampen overtime AI exposure.

It is due to the reliance on self-report instruments that there is the possibility of common-method variance despite the statistical adjustments that have been made. In the future studies, objective measures of AI integration, including the actual utilization measures or the performance results, should be included with the psychological measures. In addition, the snowball sampling method helped to reach a diverse group of educators, which is why this approach was effective; however, it could have led to selection bias because more active people in the professional networks or technology platforms might have been included in the sample. Further studies would be enhanced by the use of stratified random sampling in the representation of the differing educational institutions and different technological preparedness.

The relationships discussed here may probably be predetermined by cultural and contextual factors, but the current sample was limited to a specific geographical and linguistic environment. The research must be cross-cultural and explore whether the linkages between job crafting and technological self-efficacy have similar effect on various educational systems, attitudes towards technological use in different cultures, and the levels of institutional support towards use of AI. Contrasting research in the countries with varying rates of educational technological use may provide beneficial results in assessing the impact of the societal background on the personal attitude towards the AI implementation.

Further studies also require other moderating and mediating factors that might determine the nexus between AI awareness and educator well-being. Such variables as organizational support, collaboration with peers, leadership approach to technology, and a particular approach to AI implementation can be central in deciding whether AI will be a demand or a resource. Qualitative research may be complementary to quantitative studies where it would be possible to offer comprehensive and contextual information about how teachers feel about and conceptualize AI integration in their teaching practice.

Intervention research is one of the areas of the future inquiry which is especially promising. Research measuring the effectiveness of various professional development models including those focusing on technological skills learning and those focusing on psychological adaptation strategies could underpin evidence-based programs to support teachers. Furthermore, the studies of the most appropriate time and order of the AI integration efforts could help educational facilities to reduce the negative psychological effects to the fullest and the positive outcomes of technological innovation.

Conclusion

The current research produces new information on the issues that instructors face when they have to overcome psychological barriers related to the use of AI in the classroom. It has been proven already that even simple exposure to artificial intelligence may serve as a considerable occupational stressor, often leading to emotional exhaustion in teachers. The consequences of these results are worth noting: strong support mechanisms should be established in advance when rolling out technologies are done. On the other hand, job-enriching programs that develop technological self-efficacy turn out to be an effective moderator of the strain caused by AI and thus safeguard the welfare of teachers. Overall, the successful implementation of AI in schools goes beyond the characteristics of hardware and software; it requires a parallel emphasis on the emotional state of educators and their professional growth.

In practice, it is evident that institutions have to focus on building technological confidence of teachers with thorough training that does not focus on the procedural training only, but promotes intrinsic self-efficacy. At the same time, the development of the culture that promotes the autonomy of the job redesign may enable the teachers to be more active instead of giving up to the modernized technological environment. Administrators should also appreciate that adopting AI with no thought to the psychological impact may undermine the morale of teachers and by implication, the overall learning process of the student.

In future, it cannot be argued that AI will not infiltrate education regardless of the contingencies associated with situations. We recommend that teacher can easily navigate as well as thrive in this technologically enriched environment with appropriate protective frameworks and adaptive mechanisms in place. The most important solution is to consider AI as an addition to human teaching and not a substitute. Having a high level of technological skills and an active attitude towards job redesign, AI can promote the teaching profession instead of de-professionalizing it. This critical period in the development of education demands that the welfare of teachers should be placed at the core of any attempt that would be made to embrace new technologies.

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