HUMAN–AI INTERACTION IN GRADUATE ACADEMIC WORK: A JOB DEMANDS-RESOURCES CONCEPTUALIZATION OF SATISFACTION AND EMOTIONAL EXHAUSTION

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ABSTRACT

Artificial Intelligence (AI) technologies are increasingly embedded in graduate academic work, shaping how faculty and students perform cognitive, analytical, and knowledge-based tasks. As AI tools become integrated into writing, research, and instructional activities, human–AI interaction has emerged as a central feature of contemporary academic work environments. However, existing research has largely focused on AI adoption and technological capability, with limited attention given to how ongoing human–AI interaction influences well-being experiences in academic contexts. Drawing on the Jobs Demands-Resources (JD-R) framework, this conceptual paper develops a model that links human–AI interaction to student learning satisfaction, faculty job satisfaction, and emotional exhaustion. This paper advances propositions and outlines directions for future empirical research in graduate academic settings.

KEYWORDS

human–AI interaction, JD-R model, job satisfaction, emotional exhaustion, higher education

1. INTRODUCTION

Artificial Intelligence (AI) technologies have rapidly become embedded in graduate academic work and learning environments [1], [2], [3]. Tools such as generative assistants, language models, and intelligent feedback systems are increasingly used by students and faculty to support writing, analysis, information synthesis, and instructional design. As these tools have become more accessible and normalized, their use has shifted from experimentation to routine academic practice. Graduate students now regularly use AI tools to draft manuscripts, organize ideas, and support research tasks, while faculty use them to assist with course design, feedback generation, and scholarly productivity [4], [5]. As a result, human–AI interaction has become an increasingly salient part of academic work in higher education [5], [6].

From a Human Resources Development (HRD) perspective, this shift raises important questions about how emerging technologies shape learning, well-being, and performance. HRD scholarship has long examined how work design, learning environments, and developmental resources influence individual capability and organizational effectiveness, making academic work a relevant context for examining AI-enabled work experiences. Graduate academic work provides a particularly relevant context because students and faculty engage in cognitively demanding, self-directed, and knowledge-intensive tasks that mirror those found in broader professional environments [6], [7].

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Understanding how human–AI interaction relates to satisfaction and emotional exhaustion is particularly important for HRD because these constructs are linked to engagement, persistence, performance, and long-term professional development [7]. AI tools may support academic work by reducing cognitive burden, improving efficiency, and enhancing perceived competence. At the same time, AI may introduce ambiguity, evaluative pressure, and cognitive overload that may contribute to strain and reduced overall satisfaction. These contrasting possibilities suggest that AI should be examined not only as a technical tool but also as a meaningful feature of contemporary academic work.

Although research on AI in education has expanded rapidly, much of the existing literature has focused on AI adoption, technological capabilities, or ethical concerns, such as academic integrity [8]. Less attention has been paid to how ongoing human–AI interaction operates in everyday academic work and how it relates to well-being outcomes. In particular, limited conceptual and empirical work has examined human–AI interaction through established HRD and organizational frameworks such as the Jobs Demands-Resources (JD-R) model [6].

The JD-R framework offers a useful lens for understanding how work conditions operate as resources that support motivation and performance or as demands that require effort and may lead to strain [9]. However, AI has not been sufficiently conceptualized within this dual-role framework in graduate academic settings. Additionally, little work has examined how human–AI interaction relates to student learning satisfaction, faculty job satisfaction, and emotional exhaustion, or how these outcomes may co-occur in contemporary academic environments. This instability limits understanding of whether human–AI interaction enhances or undermines well-being in higher education contexts.

Accordingly, this paper is conceptual rather than empirical. It develops a theoretically grounded JD-R framework that positions human–AI interaction as a work experience that can function as either a job resource or job demand in academic graduate work. This paper links human–AI interaction to satisfaction and emotional exhaustion and provides a foundation for future empirical research in academic contexts.

2. Purpose Statement

The purpose of this conceptual paper is to develop a JD-R-based framework to understand how human–AI interaction functions as both a job resource and a job demand, within graduate academic work. Explicitly, this paper proposes a set of conceptual relationships linking human–AI interaction to student learning satisfaction, faculty job satisfaction, and emotional exhaustion, and examines how AI-related perceptions act as boundary conditions that may strengthen or weaken these relationships. By advancing a theoretically grounded model, this paper responds to the need for the HRD scholarship to better understand the implications of AI integration for learning and well-being in academia. The model also provides a foundation for future empirical research that can test these relationships in academic settings [8].

3. Theoretical Framework

Drawing on the JD-R framework, this paper conceptualizes human–AI interaction as a dual-role construct that can function as a resource (e.g., providing cognitive support, efficiency, and feedback) or as a demand (e.g., introducing ambiguity, cognitive load, and performance pressure) [10], [11]. The model proposes that when AI is experienced as a resource, it will be positively associated with student learning satisfaction and faculty and job satisfaction, whereas when experienced as a demand, it will be associated with emotional exhaustion [12].

While the JD-R model has been broadly applicable to digital work and technostress contexts [3], the current paper extends this framework by conceptualizing human–AI interaction as a dual-role construct that can serve as both a job demand and a job resource within the same operational environment. Unlike standard technologies, AI systems introduce adaptive, generative, and semi-autonomous capabilities that reshape how tactical work is performed rather than simply supporting it. This distinction is critical, as it suggests that AI may alter the balance of resource demands in ways not fully captured by prior JD-R applications. By unambiguously modeling these dual roles and their relationship to emotional exhaustion and job satisfaction in graduate academic work, this paper provides a novel theoretical extension of the JD-R framework.

In addition, the model positions satisfaction and emotional exhaustion as contemporaneously related indicators of well-being, reflecting individuals' current experiences from an academic perspective. Finally, AI-related perceptions and patterns of use are conceptualized as boundary conditions that may shape the strength and direction of these relationships. These conceptual linkages form the basis for the propositions advanced in this paper and for the measurement proposed in subsequent research.

AI is becoming increasingly embedded in academic work and learning, reshaping how faculty and students complete tasks, process information, and engage in knowledge production [13]. The JD-R model provides a systematic lens for examining how conditions within work and learning environments influence individual outcomes. The model distinguishes between job demands—such as workload, time pressures, and emotional strain—that can contribute to emotional exhaustion and job resources—including autonomy, feedback, and social support—that are associated with higher job satisfaction and may alleviate the effects of demands [10], [14]. Over the past two decades, the JD-R model has been widely applied across sectors, including healthcare and information technology, to explore how job characteristics shape employee outcomes [15]. Given the rapid and widespread adoption of AI in higher education, applying the JD-R framework offers a timely and appropriate approach to understanding how human–AI interaction influences faculty and students as they carry out their academic work and progress through graduate studies.

3.1. AI as a Resource

From a JD-R perspective, AI may be conceptualized as a resource by reducing workload, improving efficiency, and supporting cognitive performance in academic tasks [14], [16]. As a resource, AI can assist faculty and students in numerous ways. For faculty managing high-volume responsibilities, integrating AI into routine aspects of their roles can help streamline workflows. For example, AI tools can support the development of lecture outlines and syllabi, generate ideas for refreshing instructional methods, enhance creativity in designing assessments, and help in drafting grading criteria [17]. While previous research has emphasized the efficiency and performance-enhancing benefits of digital tools (e.g., [16], [17]), much of this work treats technology as a stable and predictable resource. However, AI differs from usual technologies in its generative and adaptive capabilities, which may introduce variability in outcomes and require more active user engagement. As a result, the role of AI as a resource may be more complex and context-dependent than previously assumed.

Students may also benefit from AI as a resource to support their academic work processes [18]. AI can help them organize and synthesize references to strengthen and better structure their writing, generate new research concepts, and improve the clarity and coherence of their work by offering examples of alternative phrasing and structure. In both cases, AI has the potential to mitigate stress by reducing the cognitive and administrative burdens of academic work.

Prior research on technology-supported work suggests that digital tools can serve as cognitive resources, enhancing efficiency and supporting complex knowledge work [19], [20]. In academic environments, AI systems may reduce time spent on routine cognitive tasks such as drafting, editing, and organizing information, thereby enabling individuals to devote more attention to higher-order thinking and analytical work. Within the JD-R framework, such forms of technological resources support performance and enhance perceived effectiveness in task completion [21]. Virtual support for routine or tactical tasks may provide meaningful relief, allowing faculty to devote more time to teaching and scholarship and enabling students to accelerate their research and writing. When used ethically and intentionally, AI may enhance efficiency, support performance, and contribute to a more sustainable and satisfying academic work experience.

In this context, AI-related resources extend beyond efficiency gains to include cognitive augmentation, decision support, and enhanced task flexibility. These capabilities may increase perceived autonomy and enable individuals to focus on higher-order academic activities, thereby strengthening the motivational pathway within the JD-R framework. At the same time, the dynamic and adaptive nature of AI suggests that its resource value is contingent on how effectively users integrate it into tactical academic workflows.

3.2. AI as a Demand

Faculty may also worry about AI generating inaccurate information or inadvertently “training” AI systems in ways that conflict with institutional expectations [22], [23]. These concerns can create ethical tensions in work relationships and in their interactions with university policies. [23]. In academic contexts, these pressures may contribute to job strain, internal conflict, and reduced satisfaction, underscoring the importance of understanding AI not only as a resource but also as a potential source of stress.

Although existing research on technostress highlights the potential for digital tools to increase cognitive and emotional strain (e.g., [3], [23], [24]), much of this literature focuses on system overload, complexity, or constant connectivity. AI introduces unique forms of demand related to uncertainty, accountability, and the need for rigorous evaluation of generated outputs due to agreeableness. These distinctions suggest that AI-related demands may not be fully captured by existing technostress frameworks.

Emerging research on technology-enabled work suggests that digital tools can also introduce new forms of strain, often described as technostress or technology-induced workload [3], [25], [26], [27]. When individuals must learn new systems, monitor automated outputs, or verify algorithmically generated information, the anticipated efficiency gains of technology may be offset by any additional cognitive demands. In academic environments, the need to critically evaluate AI-generated responses, ensure accuracy, and align AI-assisted work with institutional expectations may require sustained attention and effort. Within the JD-R framework, such experiences represent job demands that draw on cognitive and emotional resources and may contribute to emotional exhaustion when individuals perceive them as difficult to manage or ambiguous [2]. In this context, AI-related demands are driven not only by workload but also by the cognitive and evaluative effort required to interpret, verify, and integrate AI-generated outputs into academic tasks. This distinction highlights how AI introduces qualitatively different forms of job demands compared to traditional academic work, particularly through increased ambiguity, responsibility, exhaustive evaluation and analysis, and decision-making complexity.

Beyond its functional role as a demand or resource, AI use in academic work also raises important ethical considerations that may shape how individuals experience its impact [28], [29].

Issues such as academic integrity, authorship responsibility, transparency in AI–assisted writing, and the potential erosion of scholarly autonomy add layers of complexity to human–AI interaction. These ethical tensions may influence how individuals perceive and engage with AI, potentially amplifying both its demand–related and resource–related effects. As such, understanding AI in academic contexts requires not only a functional perspective but also consideration of ethical implications embedded with its use [30].

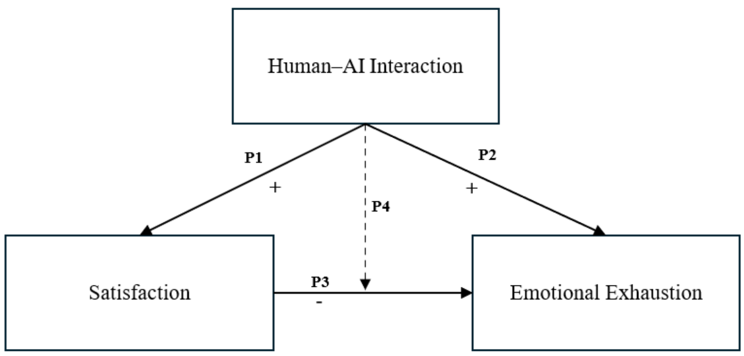
4. CONCEPTUAL RELATIONSHIPS

Building on the initial phase of AI adoption documented in prior work, the present paper shifts focus to the ongoing reality of human–AI interaction in graduate academic work. As AI tools have become embedded in writing, analysis, and learning, their role can no longer be understood solely as a novel technology but rather as a recurring feature of academic work. Drawing on the JD-R framework, human–AI interaction is conceptualized as a dual-function characteristic that may operate as either a job or learning resource or a job or learning demand. In turn, these perceptions could be associated with key well-being and performance-related outcomes, including satisfaction and emotional exhaustion [11], [8]. Accordingly, the present paper advances a set of conceptual relationships and proposes that these associations should be empirically examined in graduate academic contexts using cross-sectional survey designs.

The conceptual relationships proposed in this paper are summarized in Figure 1, which presents the proposed model in which human–AI interaction influences satisfaction and emotional exhaustion and moderates the relationship between satisfaction and emotional exhaustion with the JD-R framework.

Figure 1

Conceptual Model of the Connection Among Human–AI Interaction, Satisfaction, and Emotional Exhaustion



Note. P1=proposition 1, P2=proposition 2, P3=proposition 3, P4=proposition. Please refer to Section 5. Propositions.

4.1. AI as a Job Resource in Academic Work

Beyond AI adoption, AI can serve as a valuable resource for job and learning for students and faculty engaged in academic work [13], [31]. Particularly, AI tools can support writing, analytical reasoning, and information processing by providing real-time feedback, structural guidance, and language refinement. These capabilities may reduce cognitive load, improve task efficiency, and enhance perceived competence and task effectiveness during academic activities, including drafting manuscripts, preparing coursework, or synthesizing complex materials [32].

As AI systems have advanced (e.g., ChatGPT, Claude, CoPilot, Grammarly), their capacity to provide immediate, iterative feedback may also strengthen users' sense of control and mastery of the task [33]. Within the JD-R framework, such gains in efficiency and cognitive support can function as job resources that enhance motivation, engagement, and ultimately job or learning satisfaction [10].

Accordingly, human–AI interaction may positively contribute to student and learning satisfaction, as well as faculty job satisfaction, by facilitating task completion, improving perceived performance quality, and reducing time-related pressures in academic work contexts. Thus, within the JD-R framework, human–AI interaction is theorized to serve as a job resource that enhances satisfaction among both students and faculty [34].

4.2. AI and Emotional Exhaustion

Although human–AI interaction can function as both a job and a learning resource, it may also be experienced as a job demand characterized by cognitive overload, ambiguity, and performance pressure [35]. For both graduate students and faculty, engaging with AI tools often requires learning new prompt strategies, monitoring output quality, and determining when AI assistance is appropriate within academic norms. These activities introduce additional cognitive and regulatory demands beyond the core academic task itself [36]. For users in particular, uncertainty about how to effectively use AI tools may heighten perceived effort, time, and pressure, especially when interacting with AI under tight deadlines or high-performance expectations.

Even for more experienced users, interacting with AI systems may require ongoing vigilance [2]. Users must assess the credibility of AI-generated responses, reconcile conflicting outputs, and verify the accuracy of the information generated. Within the JD-R framework, these requirements can be conceptualized as job demands that draw on cognitive and emotional resources. When individuals must continuously evaluate, edit, and validate AI outputs, the anticipated efficiency gains of AI may instead increase mental workload [37].

When AI interaction requires additional effort rather than alleviating it, interaction may contribute to exhaustion. In the JD-R terms, this reflects a health-impairment process in which reported demands deplete energetic resources and are associated with strain. Accordingly, human–AI interaction may function as a job demand that contributes to emotional exhaustion among both students and faculty when it introduces ambiguity, potentially affecting cognitive workload, or intensifying performance pressures within academic contexts [38].

4.3. Satisfaction and Emotional Exhaustion (Contemporaneous Associations)

Within the JD-R framework, job and learning satisfaction, and emotional exhaustion represent two central indicators of well-being that may co-occur at a given point in time [39]. Rather than assuming a temporal sequence, the present model conceptualizes satisfaction and emotional exhaustion as contemporaneously related outcomes reflecting individuals' current experience of academic work and learning conditions. When individuals perceive their work or learning environment as supported, manageable, and effective, they are more likely to report higher satisfaction and lower exhaustion [40]. Conversely, when demands are perceived as ambiguous, cognitively taxing, or pressure-inducing, individuals may report lower satisfaction and higher emotional exhaustion. In this sense, satisfaction and emotional exhaustion function as parallel, related indicators of well-being within academic contexts.

Importantly, the strength of this relationship may vary with the nature of human–AI interaction. Within JD-R, the balance of resources and demands is not static; rather, it is shaped by contextual features of a work environment [41]. The extent to which individuals use AI tools, and how they experience those interactions, may alter the degree to which satisfaction and emotional exhaustion co-occur. For example, when AI functions as a resource that supports efficiency and clarity, the negative association between satisfaction and exhaustion may be attenuated. In contrast, when AI interaction introduces ambiguity, cognitive load, or evaluative pressure, the inverse relationship may be strengthened [42]. Consequently, future empirical research should operationalize satisfaction and emotional exhaustion as cross-sectional outcomes and examine human–AI interaction as a moderating variable shaping their association among graduate students and faculty.

In organizational and educational research, satisfaction and emotional exhaustion are often examined as related indicators of well-being [43], [45]. Higher levels of satisfaction typically reflect positive evaluations of work or learning environments, whereas emotional exhaustion reflects the depletion of psychological resources resulting from sustained demands [39]. Although these constructs represent distinct experiences, they frequently co-occur within knowledge-based work contexts where individuals must balance cognitive demands with perceived support and resources.

4.4. The Role of AI as a Boundary Condition

Within the JD-R framework, the effects of work characteristics on well-being are not uniform; rather they vary according to contextual and perceptual factors that shape how those characteristics are experienced [11]. In the context of graduate academic work, human–AI interaction may serve as a boundary condition that influences the strength and direction of associations between satisfaction and emotional exhaustion [45]. Specifically, the extent to which AI is perceived as supportive, efficient, and cognitively helpful, rather than ambiguous, effortful, or evaluatively demanding may shape how individuals experience academic work at a given point.

When human–AI interaction is experienced primarily as a resource that provides clarity, feedback, efficiency, and cognitive support, the negative association between satisfaction and emotional exhaustion may be attenuated [46]. Under these conditions, individuals may experience high satisfaction and lower levels of exhaustion, because AI use facilitates task completion and reduces time-related pressures. In contrast, when human–AI interaction is experienced as demand-characterized as ambiguity, verification requirements, cognitive overload, or performance pressure, the negative association between satisfaction and emotional exhaustion may become stronger. Under these conditions, individuals may report lower satisfaction and greater exhaustion because using AI effectively requires additional cognitive effort and ongoing evaluation in academic work.

Thus, within a cross-sectional framework, human–AI interaction can be conceptualized as a moderating factor that shapes the contemporaneous relationship between satisfaction and emotional exhaustion among graduate students and faculty [10]. This perspective suggests that differences in how AI is perceived and used are likely to influence how these well-being indicators co-occur in academic contexts. Empirically examining this moderating role represents an important next step for understanding the implications of human–AI interaction for well-being in graduate education. Based on the theoretical arguments outlined above, the following propositions are advanced to guide future empirical investigation.

5. PROPOSITIONS

Building on the JD-R framework and the conceptual arguments developed above, the following propositions specify the expected relationships among human–AI interaction, satisfaction, and within academic work and learning contexts. These propositions are intended to guide empirical examination using cross-sectional designs that capture contemporaneous associations among constructs.

5.1. Proposition 1:

Consistent with JD-R theory, human–AI interaction may function as both a job resource and a learning resource by providing cognitive support, feedback, and task efficiency. When individuals perceive AI tools as facilitating task completion, enhancing understanding, and improving the quality of performance, these experiences are expected to be associated with higher satisfaction in academic roles.
Proposition 1 (P1):
Human–AI Interaction will be positively associated with (a) student learning satisfaction and (b) faculty job satisfaction.

5.2. Proposition 2:

At the same time, human–AI interaction may be experienced as a job demand when it introduces ambiguity, cognitive load, monitoring effort, or performance pressures. Under such conditions, interacting with AI systems may require additional regulation, evaluation, and verification, which can be strain-inducing and fatiguing.
Proposition 2 (P2):
Human–AI interaction will be positively associated with emotional exhaustion among both students and faculty when experienced as a job demand.

5.3. Proposition 3:

Within the JD-R framework, satisfaction and emotional exhaustion represent contemporaneous indicators of well-being that may co-occur in academic environments. Perceptions of resource availability and manageable demands are expected to correspond with higher satisfaction and lower exhaustion, whereas perceived strain and overload are expected to correspond with lower satisfaction and higher emotional exhaustion.
Proposition 3 (P3):
Satisfaction and emotional exhaustion will be negatively associated with one another within academic contexts.

5.4. Proposition 4:

Importantly, the role of human–AI interaction may extend beyond direct associations to shaping the strength of the relationships between satisfaction and emotional exhaustion. When AI interaction is experienced as a resource (e.g., enhancing efficiency, clarity, or competence), it may weaken the negative association between satisfaction and emotional exhaustion. Equally, when AI interaction is experienced as a demand (e.g., increased ambiguity, monitoring effort, or cognitive load), it may strengthen this relationship.
Proposition 4 (P4):

Human–AI interaction will moderate the relationship between satisfaction and emotional exhaustion, such that the direction of satisfaction will have a positive association, and the direction of emotional exhaustion will have a negative association.

These propositions provide a framework for the measurement strategy and empirical examination outlined in the following section.

6. MEASUREMENT AND DIRECTIONS FOR FUTURE RESEARCH

6.1. Measurement

To advance empirical inquiry into human–AI interaction within graduate academic environments, the present conceptualization requires the operationalization of four primary constructs: (a) human–AI interaction/use, (b) AI-related perceptions as job resources or demands, (c) satisfaction (student learning satisfaction and faculty job satisfaction), and (d) emotional exhaustion [9].

6.1.1. Human–AI Interaction/Use

Human–AI interaction may be operationalized as the frequency and perceived intensity of engagement with AI-enabled tools (e.g., generative AI systems such as ChatGPT, Copilot, or Grammarly). Measures may include self-reported frequency of use, types of academic tasks supported (e.g., writing, analysis, feedback), and perceived reliance on AI tools in academic work [2]. In addition to frequency of use, researchers may also assess the nature of human–AI interaction, including whether AI tools are used primarily for information retrieval, writing assistance, data analysis, or instructional support [2]. Capturing both frequency and perceived reliance on AI tools provides a more nuanced understanding of how individuals integrate AI into their academic work.

6.1.2. AI as a Job Resource and Demand

Consistent with the JD-R framework, AI-related perceptions should be assessed along two dimensions: (a) AI as a resource (e.g., cognitive support, efficiency, clarity, feedback) and (b) AI as a demand (e.g., ambiguity, verification burden, ethical concern, performance pressure). Existing attitudinal AI scales (e.g., AI-positive/AI-related optimism and AI-related concern/fear) may be adapted to reflect academic work settings [47]. Measuring AI as both a resource and a demand allows researchers to capture the technology's dual role within the JD-R framework. Individuals may concomitantly experience AI as a tool that enhances efficiency while introducing uncertainty, additional cognitive effort, or evaluative pressure.

6.1.3. Satisfaction

For graduate students, satisfaction may be conceptualized as learning satisfaction, reflecting perceived effectiveness, engagement, and fulfilment in academic coursework and research activities. For faculty, satisfaction may be operationalized as job satisfaction, reflecting overall commitment to teaching, research, and academic responsibilities. Brief, validated measures, such as the Michigan Organizational Assessment Questionnaire (MOAQ) or domain-specific learning satisfaction scales, are important [48]. In academic contexts, satisfaction may reflect individuals' overall evaluation of their learning or work environment, including perceptions of autonomy, support, and effectiveness in completing scholarly tasks. Such measures capture individuals' broader appraisal of their academic experience at a given point in time.

6.1.4. Emotional Exhaustion

Emotional Exhaustion is a core subscale of burnout and can be assessed using established scales (e.g., the Maslach Burnout Inventory (MBI)-Emotional Exhaustion Subscale), adapted for academic work environments [49]. Emotional exhaustion is a core dimension of burnout and reflects feelings of emotional and cognitive depletion from sustained demands. Within academic environments, these demands may stem from heavy workloads, cognitive strain, and the pressures of scholarly productivity.

All constructs may be measured using Likert-type response formats. Internal consistency (e.g., Cronbach's alpha) and construct validity should be evaluated prior to hypothesis testing.

6.2. Directions for Future Research

The present conceptual model is designed to guide cross-sectional empirical testing of the relationships among human–AI interaction, satisfaction, and emotional exhaustion in graduate academic environments [14].

Future research will empirically examine the contemporaneous associations among these constructs, testing whether:

- Human–AI interaction is positively associated with satisfaction,
- Human–AI interaction is positively associated with emotional exhaustion when perceived as a demand,
- Satisfaction and emotional exhaustion are inversely associated at a given point in Time, and
- Human–AI interaction moderates the strength of the association between satisfaction and emotional exhaustion.

A cross-sectional design and, in later research, a longitudinal design are appropriate for capturing individuals' current perceptions of AI use and well-being, consistent with JD-R research examining perceived work and psychological experiences at a given point in time.

Future research beyond the proposed cross-sectional design may extend this work further by:

- Examining differences between student and faculty populations,
- Investigating discipline-specific variation in AI,
- Exploring organizational or program-level norms around AI use, and
- Incorporating multi-wave or longitudinal designs to examine temporal dynamics

Altogether, these directions position human–AI interaction as an emerging and meaningful construct within HRD scholarship.

This work has several limitations that should be acknowledged. First, this paper is conceptual and does not provide empirical testing of the proposed relationships. Second, the framework is focused specifically on graduate academic work and may not generalize to all educational or organizational contexts. Third, the paper conceptualizes AI broadly, and future research may need to distinguish between different types of AI tools and levels of AI integration. Despite these limitations, this paper provides a theoretical basis for future empirical research on human–AI interaction and well-being in academic work environments.

7. THEORETICAL AND PRACTICAL CONTRIBUTIONS TO HRD

7.1. Theoretical Contributions

This paper advances HRD scholarship by making three theoretical contributions. First, it extends the JD-R framework by positioning human–AI interaction as a dual-nature construct that can function simultaneously as a job resource and a job demand within academic work. Second, the paper contributes to the emerging literature on AI in higher education by shifting the focus from AI adoption to human–AI interaction and its experiential and perceptual dimensions, which may be more directly linked to well-being outcomes. Third, the paper integrates satisfaction and emotional exhaustion as concurrent indicators of well-being in AI–moderated academic work, providing a theoretically grounded framework for understanding how human–AI interaction may contribute to both positive and negative academic work experiences.

Collectively, these contributions position human–AI interaction as an important construct within HRD scholarship and extend existing work on technology and learning by integrating AI into established organizational and learning frameworks. By framing AI as a work experience rather than merely a tool, this paper provides a foundation for future research examining how emerging technologies shape well-being, performance, and learning in academic and knowledge work environments.

7.2. Practical Contributions

In addition to theoretical contributions, this work offers several practical implications for HRD professionals, faculty, developers, and academic leaders. First, recognizing AI as both a resource and a demand underscores the importance of structured training and guidance on effective AI use. Institutions ought to support students and faculty in developing competencies in prompt design, the critical evaluation of AI outputs, and the ethical use of AI tools.

Second, academic programs may benefit from establishing clear norms and policies regarding AI use in coursework, research, and instructional activities. Ambiguity regarding appropriate use can contribute to cognitive strain and performance pressure; thus, transparent guidelines may reduce uncertainty and support positive well-being experiences.

Third, HRD practitioners and faculty developers can leverage AI as a learning support tool to enhance satisfaction, efficiency, and perceived competence, while also monitoring for overreliance or cognitive overload that may contribute to emotional exhaustion. Finally, understanding the relationship between satisfaction and emotional exhaustion in AI-enabled academic environments enables institutions to design effective interventions that support performance and well-being, aligning with HRD's broader mission to enhance human development and learning in technology-rich environments.

8. CONCLUSION

This paper conceptualized human–AI interaction as a work experience embedded within academic work that may function as either a job resource or job demand within the JD-R framework. The proposed model suggests that human–AI interaction may influence satisfaction and emotional exhaustion directly and may also moderate the relationship between satisfaction and emotional exhaustion. By positioning human–AI interaction as part of the work experience rather than solely as a technological tool, this paper contributes to the JD-R and HRD literature by expanding the conceptualization of technology-enabled work in relation to well-being experiences. The conceptual model and propositions provide a foundation for future empirical research examining AI-enabled academic work and well-being outcomes across different roles and institutional contexts. As AI continues to reshape academic and knowledge work, understanding how human–AI interaction, satisfaction, and emotional exhaustion will become increasingly important for researchers, educators, and HRD professionals. This paper offers a conceptual starting point for examining human–AI interaction experiences and their implications for well-being and human development.

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