Journal of Computer and Education Research
J. Comp. Educ. Res., 14
dergipark.org.tr/jcer
ISSN: 2148-2896
Continuous Publishing Model
Review Article Open Access

Managing Academic Stress: A Conceptual Model Proposal on Technology and AI Usage in the Task Urgency–Stress Relationship

Merve VURAL ALLAHAM [1,*]

[1] *Istanbul Gelisim University, Istanbul, Türkiye, mvural@gelisim.edu.tr*

[*] *Corresponding Author: mvural@gelisim.edu.tr*

Article Info

Received: 17 August 2025
Accepted: 18 June 2026
Published: 01 July 2026

10.18009/jcer.1767405

Keywords: Task urgency, stress, technology usage, artificial intelligence usage, moderator role of digital tools

Publication Language: English

This article was published under the continuous publishing model.

Abstract

The increasing pressure from short deadlines and the need to complete tasks quickly is one of the primary causes of academicians' stress, especially as deadlines draw near. By enabling faster and more effective work, technology can reduce this burden. Artificial intelligence (AI) tools, in particular, can swiftly process complex information or automate repetitive tasks, saving valuable time and alleviating stress. Academicians with greater technological confidence are generally better prepared to manage demanding assignments, making workloads feel more manageable. Prior research highlights the influence of AI and technology on workplace stress but indicates the need for deeper investigation. Addressing this gap, the present study proposes a conceptual model that explores how technology usage (TU) and AI usage (AIU) shape the relationship between task urgency and stress. More specifically, the study reframes digital and AI-related capabilities not as direct stress-reducing tools, but as boundary conditions that shape how academics experience and cope with task urgency. The model aims to provide insights for both academics and professionals working in knowledge-intensive environments.

To cite this article: Vural-Allaham, M. (2026). Managing academic stress: A conceptual model proposal on technology and AI usage in the task urgency–stress relationship. *J. Comp. Educ Res.*, 14, e2614044 https://doi.org/10.18009/jcer.1767405

Introduction

Employees are under more time pressure in today's digitally heavy workplaces due to the increased pressure to finish tasks quickly and effectively. This pressure can increase stress and impair performance for people in high responsibility roles (Zhu et al., 2018). In the post-COVID-19 era, the shift toward digital platforms and remote teaching has intensified the pressure on academics. While these tools facilitate work continuity, they have simultaneously increased task urgency and digital fatigue (Watermeyer et al., 2024). Especially in knowledge-intensive professions, individuals' strategies for coping with stress are increasingly dependent on their level of technological proficiency and their capacity to integrate new digital solutions. However, realizing this potential is directly linked to individuals' attitudes toward technology, their technological competencies (Ramlawati et al., 2021), and their ethical awareness. Generative AI tools offer transformative potential for academic tasks like content generation and analysis (Choi et al., 2023); however, their uncritical usage may compromise critical thinking and elevate stress levels (Kasneci et al., 2023). Academic self-efficacy plays a crucial role in how individuals engage with AI; higher efficacy leads to more ethical and functional usage, which in turn facilitates better stress management and reduces problematic usage behaviors (Zhang et al., 2024). While the impact of AI on student productivity is well-documented (Zhang et al., 2024), there is a scarcity of research exploring how academics utilize these tools to manage stress under task urgency (Bhandari et al., 2024). This study addresses this gap by holistically examining AI and TU as moderators in the stress-task urgency relationship (Salah et al., 2024). Therefore, this study aims to address a significant gap in the literature by proposing a conceptual model that illustrates the moderating roles of both TU and AI utilization in the relationship between task urgency and stress (Cotton et al., 2024). Although previous studies have examined academic stress, task urgency, technology use, and AI adoption as separate research streams, the literature has not yet clearly explained how digital competence and AI-supported task execution condition the extent to which urgent academic tasks are transformed into stress. In particular, existing studies tend to treat technology and AI either as general productivity-enhancing tools or as sources of technostress, rather than as theoretically distinct boundary conditions in the task urgency–stress relationship. This creates an important conceptual gap: the mechanisms through which general technology usage competence and task-specific AI usage differently moderate stress formation under urgent task conditions remain underdeveloped. Addressing this gap, the present study proposes an integrated conceptual model that distinguishes the moderating roles of TU and AIU in the task urgency–stress relationship. Accordingly, this study positions TU and AIU as distinct but complementary moderators in the task urgency–stress relationship. The proposed model is expected to yield practical insights not only for academic settings but also for other cognitively demanding professional groups. This study presents a conceptual framework and recommends that the proposed relationships be tested through future empirical investigations. The insights to be derived hold the potential to guide university administrations and employers in developing applicable strategies for managing task-urgency-based stress through the integration of technology. The second section of this study elaborates on the pressure of urgent tasks in

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academic work environments and the associated psychological conditions, examining the concepts of task urgency and stress within the academic context. The third section explores the potential effects of TU and AI tools in coping with stress, focusing on their application in academic settings. Finally, the fourth section presents the conceptual model that explains the relationships among the aforementioned variables and outlines the theoretical framework upon which the model is based.

Task Urgency Pressure and Psychological Conditions in the Academic Context

Academic Profession and the Working Environment

Faculty members' responsibilities in today's academic environment extend beyond teaching to include research, publishing, academic advising, administrative duties, committee service, community engagement, and professional development (Awang et al., 2021). These growing and diverse demands make academic work highly knowledge-intensive and time-consuming. Since faculty satisfaction and engagement are closely linked to institutional performance, excessive workload may undermine both research productivity and teaching quality (Aboramadan et al., 2020). Heavy teaching loads, administrative responsibilities, personal commitments, and governance-related duties reduce the time available for sustained writing and research, while issues such as procrastination, missed deadlines, and inadequate planning further complicate academic work (Aydın et al., 2023). Workload perceptions are also shaped by rank, discipline, institutional affiliation, and governance structures. Moreover, centralized management, publication pressure, language barriers, ambiguous career paths, organizational conflicts, financial constraints, and the politicization of knowledge continue to challenge academic autonomy and productivity (Karatepe et al., 2021). Overall, academic pressure arises from the combined effect of teaching, research, administrative, and social responsibilities, highlighting the need for sustainable workforce policies.

Task Urgency

The concept of "task" is central to human information behavior research (Kim & Soergel, 2005) and is commonly characterized by dimensions such as objectivity, subjectivity, interdependence, value, perceived urgency, and complexity (Li, 2009). Among these dimensions, urgency plays a critical role in shaping information seeking and incidental information encountering, although its empirical effects remain underexplored (Erdelez & Makri, 2020). In contemporary work settings, urgency is intensified by the accelerated pace

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of the digital age, where digital tools speed up workflows, increase expectations for rapid responses, and create additional time pressure (Pritchard & Symon, 2023; Rosa, 2018). Highly urgent tasks may disrupt routines, require constant reprioritization, limit individuals' ability to extract value from information, and divert attention from long-term responsibilities (Zhu et al., 2018). Although managers expect employees to allocate time productively, employees often have limited control over urgent demands and must respond to organizational expectations (Shipp & Jansen, 2021). Thus, task urgency can be understood as a non-routine temporal condition that imposes faster delivery pressures and forces continuous reassessment of actions, priorities, and cognitive resources.

Task Urgency in Academic Environment

In academic environments, task urgency relates to the necessity of completion within a specific timeframe. Fixed deadlines such as conference paper or journal submissions are high urgency, while long-term research or flexible project proposals are low urgency. Under time pressure, academics' information-seeking behaviors change, affecting how information is accessed and used. Time pressure impacts productivity; for example, a day planned for writing can be disrupted by last-minute meetings, unexpected student or colleague interactions, or email backlogs (Kennedy & Porter, 2022). Student demands are a major source of time pressure some legitimate, others stemming from poor time management or perceived urgency. For student-centered academics, deprioritizing such requests is often difficult (Kennedy & Porter, 2022). Academic life also presents structural challenges. According to Keashly (2021), faculty members enjoy academic freedom and self-regulation within a peer-reviewed structure, yet unclear job descriptions and time management practices often complicate workloads (Goodboy et al., 2022). In this context, time pressure driven by task urgency affects not only individual productivity but also the sustainability of academic work.

Stress

Expectations for the rapid completion of tasks can significantly elevate employees' levels of occupational stress. In particular, encountering urgent demands may abruptly increase employees' workloads and responsibilities, strain their planning capacities, and disrupt work-life balance. This, in turn, can impair decision-making abilities, trigger mental exhaustion, and, over time, lead to reduced motivation and job satisfaction. Work-related stress is defined as negative emotional experiences that arise from an imbalance between job

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demands and individuals' ability to cope with those demands (Wang et al., 2020). Moreover, high levels of job-related stressors have been found to be significantly associated with both daily and weekly working hours (Salwa & Fatma, 2017). Such stress may stem from excessive workload, fear of failing to meet managerial expectations, or anxiety about not fulfilling one's own performance standards (Dutta & Mishra, 2024). Recurrent experiences of stress and prolonged exposure to challenging working conditions can eventually lead to burnout and various health problems, particularly psychological disorders (Burman & Goswami, 2018).

Stress in Academic Settings

Occupational stress among university academics has been steadily rising, driven by urgent task demands and heavy workloads from diverse responsibilities. Beyond teaching, research, and publishing, academics are often expected to take on consultancy, expert roles, and administrative tasks. According to the Job Demand–Control Model, stress risk is increased when there are high demands coupled with little control and inadequate support (Van Der Doef & Maes, 1999). Many experiences excessive workloads and lack control over scheduling or decision-making, which can result in burnout and inadequacy. The strain is increased by expanding student populations, scarce rewards, perceived unfairness, and adjusting to digitalization (Kinman, 2019). Work-life balance is further disrupted by structural changes like digital transformation, remote teaching, and accreditation requirements, which necessitate ongoing course updates and strengthen performance-based evaluations. Time pressure, role conflict, and burnout are caused by the increasing demands placed on scholars to meet performance targets, obtain funding, and publish internationally (Graça et al., 2021). In order to prevent burnout, mistakes, absenteeism, diminished loyalty, and faculty loss, institutions should establish policies that better divide workloads and lessen stress (Lee et al., 2022). While some studies deal with academic stress, many only look at burnout, ignoring its multifaceted, wider nature (Singh et al., 2020). Sustainable structural solutions are crucial because growing workloads and academic pressure have an impact on people as well as the caliber of research and instruction.

Task Urgency and Stress

In professional settings, the organization of work is largely determined by temporal structures. Different types of work exhibit different manifestations of these structures, which include explicit schedules, implicit rhythms, cycles, and cultural norms surrounding time

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use (Dille et al., 2023). A crucial part of these structures is waiting time, which varies based on the task at hand. For example, there are differences in waiting times between manual labor and knowledge-intensive work (Gasparin & Neyland, 2022). Efficiency and speed are valued in knowledge-intensive work settings. McGivern et al. (2018) use the phrase "time is money" to highlight the importance of time in this context. Waiting times haven't necessarily decreased, though, and they might even be getting longer given how quickly modern information technologies are developing (Rosa, 2014). This paradox creates pressure for employees to remain productive even during downtime, becoming a psychological source of stress (Kunzl & Messner, 2023). While employers expect employees to allocate as much of their time as possible to work, employees often resist such strict oversight. For knowledge workers in particular, the demand for speed and intensity becomes a factor that contributes to physical and mental strain (Rosa, 2014). Time influences not only individual work practices but also the structural operations of organizations. Each organization has its own unique temporal structure and characteristic tempo (Langley et al., 2013). These structures directly affect task planning, performance evaluation, and perceptions of productivity among employees. Although this phenomenon is often associated with labor exploitation in low-skilled jobs, it also poses a significant threat to knowledge workers. Practices such as extended working hours, work intensification, and performance management systems reduce the level of autonomy that knowledge workers have over their time, thereby negatively impacting their occupational well-being (Bailey & Madden, 2017).

Technology Usage and Artificial Intelligence Usage

Technology Usage

TU refers to individuals' ability to effectively and consciously utilize digital tools, encompassing proficiency in computer programs, interaction with digital platforms, and technological self-efficacy. In the literature, it overlaps with digital literacy, technological self-efficacy, digital competence, and the technology acceptance model. Task-technology fit identifies determinants such as ease of use, information quality, level of interaction, physical compatibility, time criticality, and workflow integration (Dishaw & Strong, 1998). Roles such as generating reports, drafting contracts, calculating payments, or completing training depend on organizational conditions (Fu et al., 2020). Technology may also reshape perceptions of time and workflow rhythm (Pritchard & Symon, 2023). Burton-Jones et al. (2017) outlined four themes explaining IS usage: psychological explanations, theories of

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usage dynamics, new measurement tools, and factors influencing adoption. Research also examines how individuals manage negative emotions (Beaudry & Pinsonneault, 2005) and how institutional pressures shape usage (Liang et al., 2007). Technological compatibility involves alignment with personal values, experiences, and task requirements (Karahanna et al., 2006). Adaptive Structuration Theory explains how technology design, user perceptions, and usage patterns shape organizational outcomes (Martin et al., 2022). Adoption ranges from rejection to full assimilation, influenced by perceived usefulness, user characteristics, and organizational support. Workplace communication has improved through intranet systems and external platforms (Bloom et al., 2014). Ultimately, TU is shaped by task type, organizational structure, time constraints, and perceptions of digital tools.

Technology Usage and Stress

The integration of ICT into professional life has major implications for individuals and organizations, becoming essential for survival in many sectors (Haider & Amar, 2023). Employees, including academics, report that ICT adoption accelerates decision-making and can boost revenue (Harris et al., 2022). However, technology's relationship with stress is bidirectional: it enhances efficiency and flexibility but can also raise job demands (Yener et al., 2021). Stress can influence ICT use, shaped by workload and autonomy. High demands increase pressure, but control over work can mitigate negative effects (Tams et al., 2020). Systematic reviews often focus on stress-inducing aspects of ICT, overlooking its supportive roles (Berg-Beckhoff et al., 2017). Day et al. (2010) distinguish ICT demands features that cause stress from ICT resources tools that aid task completion and foster growth. Employee perceptions are key: user-friendly tools are seen as resources, while frequent system updates create uncertainty (Ninaus et al., 2021). Clear guidelines for use can reduce ambiguity and frustration. ICT therefore operates as both a demand and a resource, depending on how it is implemented and perceived. For ICT to reduce rather than induce stress, organizational policies must align with user expectations and needs.

Use of Artificial Intelligence

AI refers to the use of computational methods to mimic human intelligence (Howard, 2019) and has gained economic and organizational importance due to its role in enhancing efficiency and productivity (Von Krogh, 2018). Incorporating techniques such as machine learning, natural language processing, and robotics, they also pose challenges, including fears and resistance among academics (Makeleni et al., 2023). Despite existing theories on

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technology adoption, research on organizational readiness for AI especially in developing countries remains limited (Dabbous et al., 2022). Generative AI systems such as ChatGPT are increasingly used to support knowledge-intensive academic tasks (Qasem, 2023). This frames integration as a pedagogical shift and emphasizes the necessity of AI literacy for both educators and students (Grájeda et al., 2024). However, issues with credibility, fabricated sources, accuracy, and dependability still exist (Lepik, 2024). Some argue for usage limits in education because an over-reliance on AI may impair creativity and critical thinking (Potter et al., 2024). Reputable databases should be used in conjunction with tools like ChatGPT to prevent dependence (Khoso et al., 2023). In summary, AI presents significant opportunities for personalized learning and improved teaching quality, but its adoption must be intentional, ethically grounded, and balanced with human oversight.

Use of Technology and Artificial Intelligence in Academic Settings

Research, writing, data analysis, lecture preparation, student evaluation, committee participation, and departmental management are just a few of the many duties that fall under the broad category of academic work. The degree of interaction with digital platforms, information quality, and ease of use are some of the factors that determine how well AI supports these activities. In academic settings, AI tools may support writing, editing, data analysis, and information organization, yet their relevance to this study lies primarily in how they assist task execution under urgent conditions (Choi et al., 2023).

The Relationship Between Technology Usage and Artificial Intelligence Usage

The relationship between TU and AIU depends not only on technical proficiency but also on the quality of user-system interaction. 58% of consumer interactions in Europe now take place through digital channels (Hajro et al., 2022), demonstrating both the potential for additional user experience enhancements and the profound integration of digital tools into daily life. Perceptions, expectations, and experiences all influence how AI systems are accepted and used over time. Intention to use and actual usage patterns are strongly correlated, according to studies on TU (Blut et al., 2022). Technology acceptance models suggest that perceived usefulness, ease of use, intention to use, trust, and facilitating conditions shape whether individuals adopt and continue using digital and AI-powered tools. The constant need to learn brought on by the rapid advancements in AI may cause resistance or stress (Wang et al., 2023). Understanding AI's fundamentals, potential, and constraints boosts self-efficacy and empowers people to take a more decisive approach to challenging tasks (Stolpe & Hallström, 2024). Adoption is further encouraged by the correlation between high technological interest and increased self-efficacy. Self-efficacy, perceived utility, and ease of use all work together to encourage active use of AI tools, and user-centered approaches and ethical awareness campaigns help to increase acceptance.

Conceptual Distinction between Technology Usage and Artificial Intelligence Usage

Although TU and AIU are often treated as overlapping constructs in the literature, this study conceptualizes them as distinct yet interrelated dimensions of digital engagement. As such, TU represents a trait-like construct, reflecting relatively stable cognitive and behavioral capabilities that enable individuals to navigate digital environments. In contrast, AIU refers to the situational and task-specific use of AI-powered tools (e.g., ChatGPT, Copilot, automated analytics systems) to perform or support work-related activities (Davis et al., 1989). Rather than representing general competence, AIU captures the operational application of intelligent systems in real-time task execution. Functionally, TU and AIU differ in their mechanisms of influence. TU primarily operates as a cognitive buffer, enhancing individuals' perceived ability to cope with task demands through increased self-efficacy and digital confidence (Bandura, 1997; Tams et al., 2020). AIU, by contrast, functions as an operational facilitator by supporting task execution, accelerating information access, and reducing time pressure. Table 1 presents a comparative view of these two concepts, outlining their theoretical foundations, functional differences, and measurement approaches.

Table 1. Differentiation between technology usage and artificial intelligence usage

Comparison Criterion	Technology Usage	Artificial Intelligence Usage
Definition	General digital proficiency and self-efficacy level of the individual	Active and functional use of specific AI applications
Scope	Broad (all digital tools, platforms, and software)	Narrow (e.g., ChatGPT, Copilot, AI-powered analytics tools)
Theoretical Basis	Digital literacy, self-efficacy theory, cognitive readiness	Technology Acceptance Perspective (TAM, UTAUT)
Variable Type	Trait-based; reflects individual capacity	State-based; observable behavior toward specific tool usage
Moderating Mechanism	Acts as a cognitive buffer to reduce stress	Alleviates time pressure by facilitating task execution
Direction of Impact	Influences perceived task coping through self-efficacy	Directly impacts task completion via technological support
Measurement Method	Self-report scales assessing digital self-efficacy	Usage frequency, type of use, system logs, or structured surveys
Temporal Stability	Relatively stable; can be improved through training	Dynamic; changes rapidly with access and exposure to AI tools
Functional Role	Enabler / moderator	Facilitator / moderator
Relevance in the Study Context	Represents the individual's "readiness" to manage urgent	Facilitates real-time task execution during urgent conditions

	tasks	
Position in the Conceptual Model	Moderator (cognitive competency buffer)	Moderator (operational facilitator)

As shown in Table 1, TU and AIU differ not only in scope but also in their mechanisms of influence. This distinction justifies their separate treatment as moderators in the proposed conceptual model.

The Role of Technology Usage and Artificial Intelligence Usage in the Relationship Between Task Urgency and Stress

Understanding how people use technology and how these behaviors affect work processes has become more crucial due to the rapid growth of ICT (Kaur & Arora, 2020). Task urgency describes assignments that have a high cognitive load and must be finished quickly; these assignments frequently lead to stress, pressure to make decisions, and burnout (Karasek, 1979; Rosa, 2018). In these situations, urgency serves as a stressor as well as a crucial backdrop for observing the effects of technology (Erdelez & Makri, 2020). The quality of information and the accuracy of decisions can be compromised when people are under time pressure and resort to shallow information-seeking behaviors, such as creating fewer and shorter queries, looking through fewer documents, and browsing less thoroughly (Crescenzi et al., 2016). Time constraints shorten the evaluation process and limit the variety of resources available, which further impacts results. Under urgent conditions, AIU is expected to weaken the positive relationship between task urgency and stress by supporting faster information retrieval, reducing repetitive task execution, and enabling more efficient use of limited time (Jarrahi, 2018). The suggested model offers a more thorough view of performance and well-being in time-sensitive situations by highlighting the importance of analyzing the urgency–stress dynamic in terms of both personal resources and digital tool interaction.

Ethical and Cognitive Implications of Artificial Intelligence Usage

In the proposed model, the moderating role of AIU should be understood as conditional rather than automatic. One of the primary risks is over-reliance on AI tools, which may reduce critical thinking and analytical engagement (Kasneci et al., 2023). In addition, AI-generated outputs may include inaccurate or fabricated information ("hallucinations"), posing risks for academic reliability and integrity (Ji et al., 2023). This creates a paradox in which tools designed to enhance efficiency may simultaneously introduce new forms of cognitive and ethical risk. From an epistemological perspective, the growing reliance on AI challenges traditional knowledge production by blurring the boundaries between human and machine generated content, raising concerns about authorship and originality (Zhai et al., 2023). Therefore, AI should not be viewed solely as a technical solution for stress management but as a socio-technical phenomenon requiring ethical awareness and responsible use. Integrating AI literacy and clear institutional guidelines is essential to ensure that its benefits do not compromise academic integrity and cognitive autonomy (Cotton et al., 2024).

In relation to the proposed model, these ethical and cognitive concerns should be understood as boundary conditions that shape the effectiveness of AIU as a moderator. Although AIU may weaken the positive relationship between task urgency and stress by accelerating information retrieval, reducing repetitive work, and supporting task execution, this effect depends on the responsible and critical use of AI tools. When academics use AI outputs without verification, become overly dependent on AI-generated content, or fail to consider issues of accuracy, authorship, and academic integrity, AIU may create additional cognitive and ethical burden rather than reducing stress. Therefore, the stress-reducing role of AIU in the proposed model should not be interpreted as an unconditional effect. Instead, AIU is most likely to function as an operational facilitator when accompanied by AI literacy, human oversight, critical evaluation, and clear institutional guidelines.

Methodology

Research Design

This study adopts a conceptual research design to develop a theoretically grounded framework explaining the relationship between task urgency and stress in academic work. Conceptual studies play a critical role in advancing emerging research areas by integrating fragmented knowledge, identifying theoretical gaps, and proposing testable relationships (Jaakkola, 2020). Given the rapidly evolving nature of artificial intelligence (AI) and its implications for academic work, empirical findings on the role of AI in task urgency and stress remain limited and fragmented. Therefore, developing a conceptual model is a necessary step to structure the research domain and guide future empirical investigations.

Literature Identification and Selection

The literature used in this study was selected through a purposive and theory-driven review strategy rather than a systematic review protocol. The aim was not to provide an exhaustive review of all studies on academic stress, technology use, or AI adoption, but to identify the theoretical and empirical streams most relevant to the development of the proposed conceptual model. Accordingly, the review focused on five interconnected bodies of literature: task urgency and time pressure, occupational and academic stress, technology usage and digital competence, AI usage and AI acceptance. Priority was given to studies that provided conceptual definitions, theoretical explanations, empirical evidence, or measurement-related insights relevant to the task urgency–stress relationship and the moderating roles of technology usage and AI usage.

Theoretical Synthesis Procedure

The conceptual model was developed through an integrative theoretical synthesis. First, the literature on task urgency and time pressure was reviewed to conceptualize task urgency as a temporal job demand that increases cognitive load, accelerates decision-making requirements, and intensifies perceived work pressure. Second, the Job Demands–Resources and Job Demand–Control traditions were used to explain why such urgent demands may increase stress, particularly when individuals experience limited control, insufficient resources, or reduced coping capacity. Third, Self-Efficacy Theory and digital competence perspectives were integrated to explain why technology usage competence may operate as a cognitive coping resource. From this perspective, academics with higher digital confidence are more likely to perceive urgent tasks as manageable and to mobilize digital tools effectively. Fourth, technology acceptance, trust-related, and AI usage perspectives were used to conceptualize AIU as a task-specific operational facilitator that may support task execution, accelerate information access, reduce repetitive work, and decrease time pressure under urgent conditions.

Conceptual Model Development

The theories used in this study are not treated as independent or parallel explanations; rather, they are analytically integrated according to the causal logic of the proposed model. The Job Demands–Resources/Job Demand–Control tradition provides the demand-side explanation by conceptualizing task urgency as a time-sensitive job demand. Self-Efficacy Theory provides the individual resource-side explanation by clarifying why technology usage competence may buffer the relationship between task urgency and stress. Technology acceptance and trust-related perspectives provide the tool-use explanation by explaining why AIU may function as an operational facilitator only when AI tools are

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perceived as useful, usable, reliable, and ethically manageable. Thus, the theoretical integration follows a sequential logic: task urgency creates demand pressure; TU strengthens perceived coping capacity; and AIU supports task execution by reducing information-processing effort and time pressure. In this way, the model connects job demand, individual coping capacity, and AI-supported task execution within a single explanatory framework.

The development of the propositions followed the same theoretical logic. The direct relationship between task urgency and stress was derived from the job demand and time pressure literature. The moderating role of TU was developed from Self-Efficacy Theory and digital competence research, which suggest that individuals with stronger technological confidence and perceived control are better able to cope with urgent digital work demands. The moderating role of AIU was developed from the literature on AI-supported task execution, which suggests that AI tools can reduce time pressure and cognitive effort when used effectively. The relationship between TU and AIU was included because general digital competence may facilitate the acceptance and effective use of AI tools.

Future Empirical Validation

This methodological approach is appropriate for the purpose of the study because the article does not aim to test empirical relationships directly, but to develop a theoretically grounded and empirically testable conceptual framework. Future research is encouraged to empirically test the proposed relationships using quantitative methods such as structural equation modeling (SEM) or partial least squares structural equation modeling (PLS-SEM), and to validate the moderating effects across different professional, institutional, and cultural contexts.

Conceptual Model and Proposed Relationships

With an emphasis on the moderating effects of TU and AIU, the conceptual model created in this study (see Figure 1) investigates the relationship between task urgency and stress. According to this model, the main cause of stress is task urgency. As separate moderators, TU and AIU have different effects on the relationship. In the proposed model, TU and AIU are treated as distinct moderating conditions. As noted earlier, TU functions as a cognitive buffer, whereas AIU operates as an operational facilitator. However, this facilitating role of AIU including human verification, ethical awareness, and critical evaluation of AI-generated outputs.

In the present model, AIU is conceptualized as a moderator rather than a mediator. This means that AIU is not treated as an intervening mechanism through which task urgency indirectly affects stress. Instead, AIU represents a task-specific usage condition that changes the strength of the relationship between task urgency and stress. Therefore, reductions in cognitive load and time pressure are used here to explain the moderating logic of AIU, not to propose a separate mediation pathway.

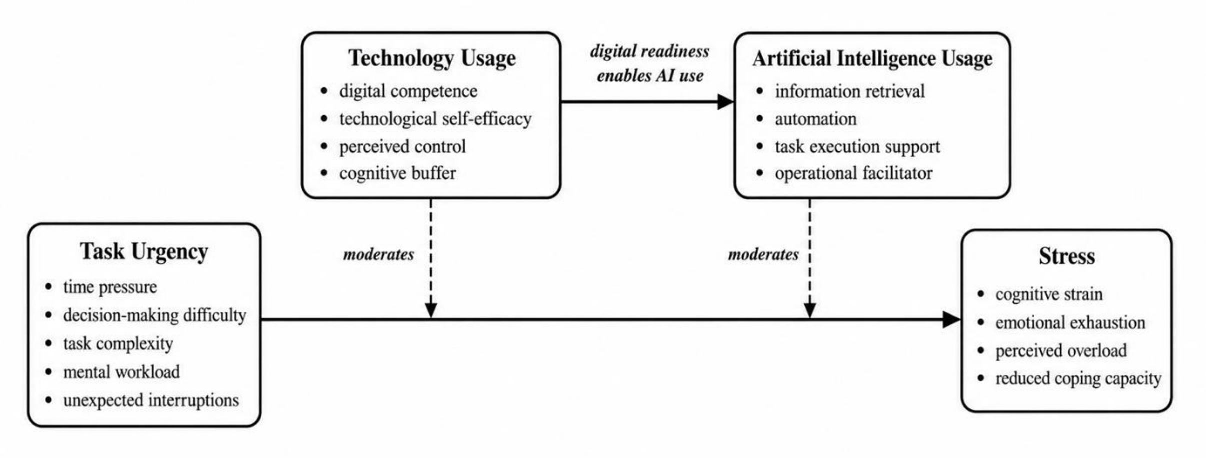

Figure 1. Conceptual model

A comprehensive summary of all the study's important variables and their theoretical foundations is given in Table 2. It describes the definition, associated sub-concepts, and theoretical foundation of each variable. This organization supports the theoretical validity of the model and makes clear how each component is conceptualized. To illustrate their different roles, the two primary moderator variables TU and AIU are shown side by side. While AIU refers to the active use of particular AI tools within task-related processes, TU represents a person's general digital skills and familiarity with technological infrastructure. AIU acts as a direct facilitator, facilitating task execution more quickly and efficiently, while TU acts as a preparatory moderator, increasing the ability to handle tasks. The psychological strain that occurs when task demands exceed available resources is captured by the variables of task urgency and stress. These are characterized by elements like cognitive load, time constraints, and difficulties making decisions. The central relationship in the model is the interplay between task urgency and stress, and TU and AIU are positioned as variables that can lessen or mitigate this pressure.

Table 2. Conceptualization of core variables and their focused theoretical foundations

Variable	Definition	Related Concepts	Conceptual Background	Analytical Role in the Model
Task Urgency	The perception of tasks	• Time pressure	• Acceleration	• Demand-side

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	that must be completed within a short period under time pressure. It directly increases stress, cognitive load, and urgency.	• Urgent decision-making • Task complexity • Mental load • Unexpected interruptions • Prioritization need	Theory in the Digital Age (Rosa, 2013) • Time Urgency Theory (Conte et al., 1995)	condition that creates time pressure and cognitive load
Stress	Psychological pressure arising from an imbalance between task demands and individual resources. Reduces mental, physical, and emotional well-being.	• Workload • Burnout • Lack of time • Decision pressure • Cognitive exhaustion • Work-life imbalance	• Job Demand-Control Model (Karasek, 1979) • Job Demands-Resources Model – JD-R (Demerouti et al., 2001)	• Strain outcome resulting from imbalance between demands and resources
Technology Usage	The individual's competence in using digital technologies, self-efficacy, and digital literacy. Serves as a cognitive buffer to mitigate stress.	• Digital literacy • Self-efficacy • Trust in technology • Adaptability • Cognitive flexibility • Learning speed	• Self-Efficacy Theory (Bandura, 1997) • Digital Competence Framework – DIGCOMP (Carretero et al., 2017)	• Individual coping resource that buffers the effect of urgency on stress
Artificial Intelligence Usage	The individual's active use of AI-based tools (e.g., ChatGPT, auto summarizers, analysis tools) to complete tasks. Enhances efficiency and reduces time pressure.	• Technology acceptance • Perceived usefulness & ease of use • Tool dependency, • Critical verification, • Human oversight, • Academic integrity, • Cognitive autonomy • Usage frequency • Time saving • Automation support	• Technology Acceptance Perspective (TAM/UTAUT) (Davis et al., 1989) • AI Acceptance Model – AIA (Gursoy et al., 2019) • Trust in Automation / AI (Hoff & Bashir, 2015)	• Tool-enabled operational facilitator that reduces task execution burden

This conceptualization not only clarifies the theoretical positions of the variables but also establishes a solid foundation for future empirical research in terms of measurement and evaluation. As a result, the explanatory power and practical applicability of the model are enhanced, offering a significant theoretical contribution to understanding individuals' technology-related behaviors.

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To enhance the theoretical clarity and testability of the proposed framework, this study formulates a set of propositions derived from the conceptual relationships among task urgency, stress, TU, and AIU. These propositions aim to provide a structured basis for future empirical validation and strengthen the explanatory power of the model.

Proposition 1 (P1): Task urgency increases stress levels in academic contexts.

Proposition 2 (P2): TU moderates the relationship between task urgency and stress such that higher levels of TU weaken the positive effect of task urgency on stress.

Proposition 3 (P3): AIU moderates the relationship between task urgency and stress such that the positive effect of task urgency on stress is weaker among academics with higher levels of task-specific AIU.

Proposition 4 (P4): TU positively influences AIU, as higher digital competence increases the likelihood of effective AI tool adoption.

To provide a more coherent overview of the proposed framework, Table 3 integrates the key constructs, their roles in the model, theoretical functions, expected relationships, and corresponding propositions.

Table 3. Proposed relationships and theoretical logic of the conceptual model

Proposition	**Proposed Relationship**	**Role in the Model**	**Theoretical Logic**	**Expected Direction**
P1	Task urgency → Stress	Direct effect	Task urgency is conceptualized as a time-sensitive job demand that increases cognitive load, time pressure, and perceived strain in academic work.	Positive
P2	Task urgency × TU → Stress	Moderating effect	TU operates as a cognitive competency buffer. Academics with higher technology usage competence are more likely to perceive urgent tasks as manageable and use digital tools effectively under time pressure.	Weakens the positive task urgency–stress relationship
P3	Task urgency × AIU → Stress	Moderating effect	AIU operates as a task-specific operational facilitator. Under urgent conditions, academics who use AI tools more actively can retrieve information faster, reduce repetitive work, and complete tasks more efficiently, thereby weakening the effect of urgency on stress.	Weakens the positive task urgency–stress relationship
P4	TU → AIU	Direct enabling effect	TU increases AIU because digitally competent academics are more likely to have the confidence, readiness, and ability to adopt AI tools effectively.	Positive

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Discussion

This study develops a conceptual model explaining how technology usage (TU) and artificial intelligence usage (AIU) condition the relationship between task urgency and stress. In academic contexts, the simultaneous execution of research, writing, supervision, teaching, and administrative responsibilities intensifies temporal pressure and increases the likelihood of cognitive and emotional strain (Awang et al., 2021; Aydın et al., 2023). Prior research shows that task urgency is closely associated with time pressure, sudden decision-making, and increased cognitive load, all of which may elevate stress levels (Rosa, 2018). Under urgent conditions, individuals also tend to adopt more superficial information-seeking strategies, examine fewer resources, and experience greater difficulty in evaluating information effectively (Crescenzi et al., 2016; Erdelez & Makri, 2020). These dynamics suggest that stress does not emerge solely from the urgency of the task itself, but also from the individual's capacity to manage information, time, and cognitive demands under pressure.

Within this framework, the proposed model shows that the task urgency–stress relationship is not uniform, but depends on the cognitive and operational resources academics can mobilize under pressure. By distinguishing TU from AIU, the model shifts the discussion from whether technology reduces stress in general to how different forms of digital engagement shape the strength of the urgency–stress relationship.

An important implication of this distinction is that TU and AIU should not be treated as interchangeable constructs. TU captures a broader readiness to engage with digital environments, whereas AIU reflects the situated application of intelligent tools during task execution. This distinction helps clarify why two individuals facing the same urgent task may experience different stress outcomes: one may benefit from general digital confidence, while another may additionally reduce task-related pressure through effective AI-supported work practices. In this sense, the model contributes to the literature by shifting the discussion from whether technology or AI reduces stress in general to how different forms of digital engagement shape the strength of the task urgency–stress relationship.

At the same time, the stress-reducing potential of AIU should not be interpreted as unconditional. Although AI tools may support academic work in areas such as literature review, writing, data analysis, and content organization, their benefits depend on responsible and critical use (Qasem, 2023). Overreliance on AI, insufficient verification of AI-

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generated outputs, and uncritical dependence on automated suggestions may create new cognitive and ethical burdens rather than reducing stress (Lepik, 2024; Potter et al., 2024). Therefore, AIU should be understood as a supportive mechanism that complements, rather than replaces, academic judgment, domain expertise, and critical thinking.

Overall, this study argues that stress under task urgency is shaped not only by external time constraints but also by the resources and competencies individuals mobilize in response to those constraints. By distinguishing TU as a cognitive-buffering condition and AIU as an operational-facilitating condition, the proposed model offers a more nuanced explanation of how academics may cope with urgent task demands in digitally mediated work environments. This perspective provides a theoretical basis for future empirical research examining when, how, and under what conditions technology and AI use can mitigate stress in high-pressure academic and knowledge-intensive settings.

Theoretical Contribution

This study contributes to the literature by developing a conceptual framework that explains how task urgency is translated into stress under different technological conditions. Rather than treating task urgency merely as a time-related pressure, the model conceptualizes it as a multidimensional stressor involving time pressure, decision-making difficulty, task complexity, mental workload, and unexpected interruptions. In doing so, the study draws on the Theory of Social Acceleration (Rosa, 2013) and Time Urgency Theory (Conte et al., 1995) to explain how accelerated work rhythms and temporal demands intensify strain in academic settings. Stress is further interpreted through Karasek's (1979) Job Demand–Control Model and the Job Demands–Resources Model (Demerouti et al., 2001), which frame stress as an outcome of the imbalance between job demands and the resources available to manage them.

The main theoretical contribution of the study lies in distinguishing TU and AIU as two technology-related but theoretically distinct boundary conditions in the task urgency–stress relationship. Grounded in Self-Efficacy Theory and the Digital Competence Framework, TU explains the cognitive readiness dimension of coping with urgent academic tasks by reflecting individuals' digital literacy, technological confidence, trust in technology, and perceived control (Bandura, 1997; Carretero et al., 2017). In contrast, AIU is informed by technology and AI acceptance perspectives and explains the operational support dimension of AI-assisted task execution under urgent conditions (Davis et al., 1989; Gursoy et al., 2019;

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Hoff & Bashir, 2015). This dual-moderator structure clarifies why technology-related resources should not be treated as a single, undifferentiated construct in explaining how task urgency translates into stress.

Another contribution of the study is its analytical integration of multiple theoretical perspectives. Instead of using these theories only as a broad descriptive background, the model assigns each theoretical lens a specific explanatory function. The Job Demand–Control and Job Demands–Resources perspectives explain the demand–strain pathway; Self-Efficacy Theory and the Digital Competence Framework explain the cognitive-buffering role of TU; and technology acceptance and trust-based perspectives explain the conditions under which AIU may function as an effective task-execution support mechanism. In this way, the model provides a theoretically structured basis for future empirical research on academic stress, digital competence, and AI-supported work in high-pressure knowledge-intensive environments.

Practical Contribution

This study moves beyond general recommendations and provides concrete, actionable guidance for higher education institutions aiming to support academics working under time pressure. Universities can introduce simple but structured "urgent-task protocols" for tasks that must be completed within 24–48 hours (e.g., last-minute reports, accreditation documents, student-related paperwork). These protocols may include step-by-step digital support suggestions, such as using AI tools for summarizing long documents, drafting initial reports, organizing scattered information, or quickly scanning relevant sources. Importantly, these tools should be positioned as assistants that save time, not as substitutes for academic judgment. Instead of broad and often ineffective digital training programs, institutions can offer short, hands-on workshops directly aligned with academics' daily needs. For example, sessions on "how to prepare a report in one hour using AI support," "how to verify AI-generated content," or "how to manage multiple urgent tasks digitally" can have immediate practical value. These trainings should be optional, flexible, and repeatable during high-pressure periods. Universities should establish clear and realistic AI usage guidelines tailored specifically to academic work. Rather than abstract ethical statements, these guidelines should clearly answer practical questions such as: In which tasks can AI be used freely? When is human verification mandatory? Who is responsible for errors in AI-assisted outputs? Providing such clarity can reduce uncertainty and prevent

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additional stress. Workload distribution should acknowledge digital inequality among academics. Not all staff have the same level of technological competence or access to tools. Therefore, during intense periods such as exam weeks, accreditation processes, or publication deadlines, task allocation can be adjusted by considering both time pressure and available digital support. In some cases, providing temporary technical assistance may be more effective than redistributing workload. Finally, departments can foster informal but powerful support mechanisms such as peer-based digital mentoring. Academics who are more comfortable with AI and digital tools can share quick tips, example prompts, or workflows with colleagues. Additionally, creating short-term “digital support hours” during peak periods where academics can get quick help with urgent tasks can significantly reduce stress. In this sense, the model proposed in this study does not only explain stress dynamics but also offers a realistic roadmap for redesigning academic work in the age of AI making it more manageable, more supported, and ultimately more sustainable.

Conclusion

This study conceptually examines how task urgency, frequently encountered in academic work environments, affects individuals’ stress levels, and the moderating roles of TU and AIU in this relationship. Based on the literature, the proposed model shows that stress is not only a result of task-related structural characteristics but is also shaped by individuals' digital competence, tool usage skills, and their interaction with technology. Task urgency increases time pressure and consequently stress, particularly among professionals with multiple responsibilities, such as academics. However, this stress is shaped by individuals' cognitive resources, digital skills, and instrumental adaptability. Overall, the study shows that TU and AIU weaken the task urgency–stress relationship through different but complementary mechanisms: one based on digital readiness and the other on task execution support. Especially in tasks involving content generation, analysis, summarization, and recommendation development, AIU may weaken the extent to which urgent academic tasks are translated into stress by supporting information retrieval, task execution, content generation, analysis, and summarization under time-sensitive conditions. Additionally, the shift in information-seeking behavior under time pressure emphasizes the importance of goal-oriented digital information strategies over incidental information encounters. In light of these findings, not only technical infrastructure and software systems but also raising individuals’ digital awareness, supporting their self-efficacy, and promoting AI literacy are of significant importance. Academic institutions should prioritize professional development programs and awareness training to ensure that employees can establish a healthy and effective relationship with these technologies. Guidance on the pedagogical and ethical use of AI tools is also critical for the sustainability of this transformation. Future studies should empirically test this conceptual model across different professional groups (e.g., healthcare, media, public administration) and cultural contexts to enhance its generalizability. Control variables such as gender, age, and experience may also be integrated into future research. Furthermore, statistically testing the moderation effects will strengthen the theoretical validity of the model.

Limitations and Future Research

This study conceptually examines the moderating role of TU and AIU in the relationship between task urgency and stress. Several limitations should be noted. First, the model, though theoretically grounded, has not been empirically tested and should be validated through quantitative methods. Second, it was developed in an academic context; testing it in other sectors (e.g., healthcare, software, finance) would enhance generalizability. Third, future research should explore potential interactions between TU and AIU, as well as the influence of individual differences such as digital literacy and institutional support. Lastly, negative consequences of AI tools, such as overdependence or reduced critical thinking, were excluded from this study's scope but should be considered in future work. Overall, the model provides a theoretical basis for understanding how digital tools can support stress management and remains open to empirical validation.

Although the proposed model focuses specifically on the task urgency–stress relationship, academic stress is shaped by a broader set of structural and institutional factors. Publication pressure, performance evaluation systems, academic job insecurity, emotional labor, administrative workload, and role ambiguity may also intensify stress in academic work environments. These factors were not included in the present model in order to maintain a focused theoretical explanation of how task urgency is translated into stress under different technological conditions. Future studies may extend the proposed model by incorporating these structural stressors as antecedents, control variables, or additional moderators to examine whether the buffering roles of TU and AIU remain significant under broader institutional pressures.

Operationalization and Future Empirical Testing of the Proposed Model

Future empirical studies should clearly operationalize the key constructs of the proposed model. Task urgency may be measured through perceived time pressure, deadline proximity, the need for rapid task completion, and the immediacy of response required by academic duties. Stress may be assessed using established perceived stress, job stress, or academic stress scales adapted to urgent academic work contexts. Technology usage should be measured as a general digital readiness construct, including digital competence, technology self-efficacy, confidence in using digital platforms, and adaptability to new technologies. In contrast, artificial intelligence usage should be operationalized as the task-specific and behavior-oriented use of AI tools, including frequency and intensity of use, type of academic task supported by AI, perceived usefulness, and trust in AI-generated outputs. Future studies may also examine perceived time saving and reduced cognitive load as explanatory mechanisms through which AIU may reduce stress under urgent task conditions. The proposed model can be tested using moderated regression analysis, PROCESS macro, covariance-based SEM, or PLS-SEM. In such designs, task urgency should be specified as the independent variable, stress as the dependent variable, and TU and AIU as separate moderators. The interaction terms task urgency × TU and task urgency × AIU would indicate whether digital competence and task-specific AI use weaken the positive relationship between task urgency and stress. To test the dual role of TU—both as an independent moderator and as an antecedent to AIU (as proposed in P4)—future studies should employ conditional process analysis (e.g., Hayes' PROCESS macro) or advanced PLS-SEM models that can simultaneously handle moderation and direct enabling effects. Future studies may also include control variables such as age, gender, academic rank, work experience, discipline, workload, institutional support, and prior AI experience.

Artificial intelligence usage should not be measured only through general indicators such as frequency of use or access to AI tools. Rather, AIU should be operationalized as a multidimensional, task-specific construct that captures the intensity, scope, depth, and quality of AI-supported task execution. In future empirical studies, AIU may be measured through indicators such as frequency and intensity of use, type of academic task supported by AI, functional depth of use, integration of AI into daily workflow, perceived time saving, and perceived reduction in cognitive load. This multidimensional operationalization would allow researchers to distinguish between superficial AI use and more advanced and task-

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integrated AI use under urgent work conditions. Furthermore, future researchers are encouraged to measure 'AI verification behavior', 'human oversight', and 'trust in AI' as distinct control variables. This separation is crucial to ensure that the operational frequency and intensity of AI use (AIU) are not confounded with users' ethical and responsible use behaviors.

Table 4. Operationalization guidelines for future empirical studies

Construct	Possible operationalization	Measurement suggestion	Conceptual role	Possible testing approach
Task urgency	Perceived time pressure, deadline proximity, need for rapid completion, immediacy of response, unexpected task interruptions	Likert-type items measuring perceived urgency, time pressure, and deadline intensity	Independent variable	Direct effect on stress
Stress	Perceived occupational/academic stress caused by urgent tasks, psychological strain, exhaustion, tension	Perceived Stress Scale, job stress scales, academic stress/adapted occupational stress measures	Dependent variable	Outcome variable
TU	Digital competence, digital self-efficacy, platform confidence	Digital competence or computer self-efficacy scales	Moderator	Task urgency × TU
AIU	Frequency and intensity of AI use, type of academic task supported by AI, perceived usefulness, trust in AI outputs, perceived AI-assisted time saving	Frequency and intensity of AI use; task type supported by AI; functional depth of use; workflow integration; perceived time saving; perceived cognitive load reduction; trust in AI outputs; verification behavior; balanced reliance on AI	Moderator	Task urgency × AIU

Acknowledgement

Due to the scope and method of the study, ethics committee permission was not required.

Author Contribution Statement

Merve VURAL ALLAHAM: *Literature review, methodology, experimental applications, statistical analyses, and interpretation of findings.*

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