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ASSESSING THE EFFECTIVENESS OF DIGITAL WELLBEING TOOLS ON STUDENT STRESS WITH INSIGHTS FROM AI CHATBOTS AND SELF-GUIDED INTERVENTIONS

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ABSTRACT
The study will address how digital wellbeing resources, chatbots based on AI, and self-managed interventions can be used in managing stress among students in a multimodal and human-centred strategy. As the use of AI-based mental support in colleges and universities gains more and more popularity, the research problem is to determine how the variables, including self-efficacy, digital wellbeing behaviors, and the use of AI chatbots, affect stress among university students. It has been implemented in terms of a quantitative research method and survey among 300 students with various academic backgrounds has been conducted. Students who were more self-efficacious and who were employed with the digital wellbeing more actively utilized AI chatbots, where the lower degree of stress also accompanied. The findings indicate that it is not enough to merely provide AI tools, but an all-encompassing strategy that will enable learners to develop self-efficacy, adopt active digital wellbeing strategies, and suggest that they engage with AI chatbots on a regular basis is the key to effective stress management. The research will be applicable in teachers and policy makers planning to explore human-based interventions of digital wellbeing in universities.
KEYWORDS: Digital Wellbeing; University Stress; Artificial Intelligence; Chatbots; selfefficacy; University; Mental Health.

INTRODUCTION

The fast evolution of the digital technologies has significantly changed the field of the higher education, specifically, the field of studying and mental health and wellbeing of students because more and more educational establishments turn to the digital options as a tool of learning and communication [1]. The modern university students have been subjected to increased academic pressure, academic competition, financial pressure and unceasing electronic connectivity all of which have nearly led to the stress, anxiety and emotional burnout to unimaginable levels [2]. The conventional campus counseling service is often small with regard to capacity, accessibility and scalability and as such, the counseling service is not capable of meeting increasing mental health demands by the students [3]. Therefore, colleges and universities are coming to embrace the adoption of digital wellbeing applications and artificial intelligence (AI) facilitated mental health appliances as the latest support systems that can be used to improve wellbeing among students [4]. The newly emerged AI-based mental health technologies (AI chatbots, and self-managed digital interventions, specifically) have proved to be the possibly exciting stress management and emotion control mechanisms of the university students [5]. These technologies use technologies that are based on machine learning and natural language processing to provide real-time emotional support, psychoeducation, mindfulness, and cognitive behavioral support [6]. The property of non-judgment and anonymity of AI chatbots is particularly appealing to students who can be stigmatized, and they can be afraid of privacy invasion and unwilling to experience face-to-face psychological counseling [7]. Consequently, AI-based digital wellbeing interventions are increasingly becoming part of mental health in institutions since they are scalable and cost-effective interventions [8]. Although they have become more popular, the facts and the statistics on the effectiveness of the implementation of digital wellbeing tools to the stress reduction among students are still scattered and inconclusive [9]. According to the research provided above, the variables that are considered to be relevant in the determination of the effectiveness of the digital mental health intervention are the engagement of users, perceived usefulness, and personalization [10]. The perception that an individual can effectively manage the challenges, i.e. self-efficacy, is an important component of engagement among the students in coping with the stress management skills and digital wellbeing devices [11]. With a greater degree of self-efficacy, students would be more active in coping mechanisms, remain active in AI-based interventions and have better mental health outcomes [12]. Moreover, the psychological wellbeing of students is staggering due to the effect of such digital wellbeing interventions as mindful use of technology, formal self-managed practices, and balanced management of screen time [13]. It has also been found that positive digital wellbeing practices correlate with less stress, better emotional regulation and academic performance and uncontrolled and excessive use of digital technologies may lead to techno-stress and digital fatigue [14]. In order to exploit the opportunities of AI-based mental health equipment, a multimodal human-centered design approach is central [15]. The humanistic design takes into account the idea of personalization, user autonomy and psychological protection which stipulates that the available digital wellbeing tools will not interfere with the available traditional approach of human support [16]. Nevertheless, the sources of empirical research to discuss the integrated effect of self-efficacy, digital wellbeing behaviors, and the use of an AI chatbot on the subject of student stress within one frame are insufficient [17]. The current literature muses on the personal attributes of technology or psyche and in this respect, it enables the visualization of the incomplete comprehension of the relationship of the two features as it exists in the environment of tertiary education [18]. To address this gap in the research, the given study will explore the prospects of digital wellbeing tools to alleviate stressfulness in students, i.e., how AI chatbots and self-guided interventions are going to impact this population of individuals with the orientation on human-focused research [19]. This research will allow testing the relationships that are present between the variables student stress, student self-efficacy, student digital wellbeing behavior, and the use of AI chatbot in a higher education institution because of the quantitative research design and the study will be added to the growing body of research on the subject of AI-based mental health interventions in higher education [20].

OBJECTIVES OF THE STUDY

This study aims to estimate the effectiveness of Digital wellbeing tools and AI chatbots in reducing the levels of stress among students by enhancing their self-efficacy. In addition, it also attempts to explore the mediating role of self-efficacy between technology-based wellbeing tools and mental health outcomes of students.

2. REVIEW OF LITERATURE

The growing incorporation of digital technologies in post-secondary education has redefined the concept of student mental health and its management [21]. The ideas of digital wellbeing, AI-based mental health care, and technology mediated stress management have become common in the recent scholarly community [22]. Although the benefits of digital wellbeing tools are commonly linked to the following aspects: better emotional regulation, better access to mental health services and better self-management, studies also point out some undesirable consequences of the change such as techno stress, digital exhaustion, and cognitive overload [23].Thus, such constructs should be operationalized attentively in order to distinguish positive digital interventions like AI chatbots and self guided mindfulness apps and harmful digital stressors [24]. There exist clear conceptual differences that allow making the role of technology in student wellbeing more precise [25].

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2.1 DIGITAL WELLBEING TOOLS IN HIGHER EDUCATION

Higher education institutions are increasingly using digital tools of wellbeing, such as mobile apps, web based systems and AI based systems, to curb the increasing levels of stress among students [26]. The tools are aimed at achieving mindfulness, emotional self awareness, stress, and adaptive coping [27]. The popularity of smartphones and learning management systems has only enhanced the usage of digital wellbeing tools, which allows access to mental health assistance 24/7 even without the use of traditional counseling services [28]. Empirical research shows that interventions administered digitally through structure can have a powerful impact of reducing stress, anxiety and depressive symptoms in university students [29]. Mindfulness exercises, journaling, breathing exercises, and cognitive behavioral modules are self directed interventions that have been demonstrated to improve emotional resilience, concentration and academic engagement [30]. The success of these tools, however, is highly determined by the level of engagement, personalization, perceived usefulness, and institutional support [31]. On the other hand, the over use of digital platforms can result in screen fatigue, fragmented attention, and poor wellbeing unless it is properly balanced [32]. These results serve to emphasise the importance of having a balanced and human centred approach towards the implementation of digital wellbeing [33].

2.2 AI CHATBOTS AND SELF-GUIDED INTERVENTIONS

AI-based mental health chatbots have been a new and fast-growing branch of digital wellbeing technologies [34]. They are based on natural language processing, machine learning, and affective computing to offer conversational support, psychoeducation, emotional monitoring, and therapeutic interventions like cognitive behavioral therapy and mindfulness [35]. AI chatbots also have such benefits as anonymity, immediacy, scalability, and cost effectiveness, which makes them especially appropriate to use with student populations that have reservations about conventional counseling services [36]. It has been indicated that regular communication with AI chatbots may decrease perceived stress, anxiety and loneliness and increase emotional awareness and self reflection [37]. Digital interventions with self guided features that happen within the chatbot platforms also enhance autonomy where students have the opportunity to manage their mental health independently [38]. Although these advantages exist, researchers give warnings against the excessive use of AI-mediated emotional support because of a lack of depth in emotions, issues of ethics in the field of data privacy, and dependence [39]. As a result, AI chatbots are best suited to work as supplements, and not alternatives to human based mental health services [40].

2.3 SELF-EFFICACY AND STUDENT STRESS

Self efficacy is a fundamental psychological concept, which plays a serious role in perception and coping behavior with regard to stress [41]. Social cognitive theory postulates that people who have greater self efficacy exhibit greater confidence in dealing with stressors and coping with challenges [42]. Self efficacy has been associated consistently with lower stress levels, emotional regulation, greater motivation and higher academic performance in academic settings [43]. Previous research findings suggest that a student who has a stronger self efficacy is more prone to proactive adoption of digital wellbeing instruments, has a higher likelihood of continuing to participate in self guided interventions, and enjoys a positive AI chatbot interaction [44]. Moreover, self efficacy, has been found to counter the adverse effect of academic pressure and digital overload as a buffering process [45]. Nevertheless, the existing literature tends to study self efficacy separately, which indicates the necessity to find integrated approaches, which would measure interactions between self efficacy and technological interventions to determine the impact of self efficacy on stress outcomes [46].

2.4 RELATIONSHIP BETWEEN DIGITAL WELLBEING TOOLS AND STUDENT STRESS

The dependence that exists between digital wellbeing tools and student stress is dynamic and context dependent [47]. According to previous literature, organized mindfulness sessions and emotional tracking and relaxation between stress, concentration, and subjective wellbeing are effective digital wellbeing activities [48]. Artificial intelligence chatbots also enhance the association by delivering customized feedbacks, dynamic learning and ongoing emotional care [49]. Nevertheless, digital wellbeing tools are based on factors including digital literacy, perceived autonomy, trust in AI systems, and institutional integration [50]. Badly constructed or too obtrusive digital tools can even exacerbate stress instead of reducing it, especially when they contribute to the techno stress or performance pressure [51]. These results highlight the significance of the introduction of digital wellbeing tools into a favorable educational environment that focuses on student agency and mental wellbeing [52].

2.5 INTEGRATED ROLE OF AI CHATBOTS, SELF-EFFICACY, AND DIGITAL WELLBEING

The current literature is moving towards the use of integrated and multimodal models involving the incorporation of psychological assets and technological interventions to improve mental health outcomes [53]. Research shows that the self efficacy improves the interest of students in AI chatbots, and regular chatbot use strengthens coping, emotional control, and self awareness [54]. This mutual connection implies that AI powered digital wellbeing technologies are best implemented when framed within a human centered design paradigm to facilitate autonomy, competence, and psychological safety [55]. Although there is an increased academic attention to these constructs, empirical studies investigating these constructs concomitantly employing quantitative models are scarce, especially in tertiary education contexts [56]. In that vein, more studies should be undertaken to understand the interaction between AI chatbots and self guided digital interventions with self efficacy and digital wellbeing behaviors to transform into the outcome of student stress [57].

RESEARCH GAP

Though the use of digital wellbeing tools and AI chatbots has been on the rise in the higher education sector, previous studies have mainly explored their individual effects on student mental health. Current research is either concentrated on self-guided digital wellbeing programs or chatbots based on AI, which does not provide much information about their combined effect on stress in students. Also, the psychological processes that are at the root of these technologies and how they influence them most notably the importance of self-efficacy have not been adequately discussed. The lack of a coherent empirical mechanism that simultaneously connects digital wellbeing tool, use of AI chatbots, self-efficacy, and student stress has led to a disjointed comprehension of technology- based wellbeing support. To fill this void, the current study constructs and empirically supports a fully-fledged framework that involves investigating the direct and indirect influences of digital wellbeing applications and AI chatbots on student stress, and self-efficacy is a mediating variable in the context of higher education.

CONCEPTUAL FRAMEWORK

The assumption of the proposed study is that digital wellbeing tool and AI chatbots can be viewed as the technology enabled intervention that enhances the psychological resources of students, especially self efficacy, which subsequently affects the level of student stress [58]. Digital wellbeing programs like self guided stress management and mindfulness applications assist students in obtaining sound coping skills,

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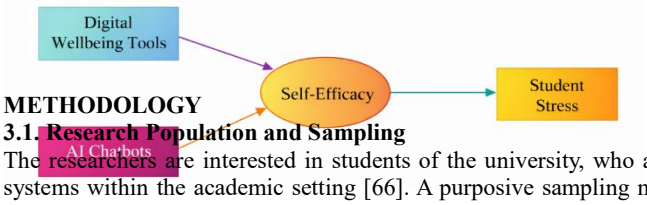
emotional regulation skills and confidence in their approach to addressing academic demands [59]. On the same note, AI chatbots offer long-term, tailored, and dynamic mental health assistance, which supports the notion of students that they can handle stress and emotional difficulties [60]. Collectively, the technologies ensure that a human centered digital wellbeing ecosystem is formed where self efficacy forms one of the psychological processes that connect technology use to stress outcomes [61].

H1: Digital wellbeing promotes positively on self-efficacy in students.
Interventions based on digital wellbeing encourage self regulation and proactive coping, thus making students more confident in their ability to deal with academic and emotional issues [62].
H2: The usage of AI chatbots has a positive impact on the self-efficacy of students.
AI chatbots enhance the perceived stress coping ability of students through personalized feedback, emotional reassurance and live-time interactions [63].
H3: The self-efficacy has a negative effect on student stress.
Students who have high self efficacy are better placed to handle stressors resulting in reduced perceived stress [64]. The empirical model based on these hypotheses allows to test a mediated relationship, according to which digital wellbeing instruments and AI chatbots indirectly influence student stress based on self efficacy [65].
The empirical framework derived from these hypotheses enables the testing of a mediated relationship, wherein digital wellbeing tools and AI chatbots indirectly affect student stress through self efficacy [65].



METHODOLOGY

3.1. Research Population and Sampling

The researchers are interested in students of the university, who actively use digital wellbeing tools and AI-based mental health support systems within the academic setting [66]. A purposive sampling methodology was used to identify participants that use digital wellbeing applications or AI chatbots to cope with academic pressure, emotional or stress-related issues frequently [67]. Purposive sampling is also very appropriate where the respondents are chosen according to their relevancy and experience relating to the phenomenon being studied thus improving the validity of the results [68].

3.2. Data Collection Process

The actual data used in conducting the research was a structured questionnaire that was created to measure how effective digital wellbeing tools and AI chatbots are in alleviating stress among students [69]. A sample of 300 university students was chosen to participate in the survey among the students of different academic disciplines [70]. The use of structured questionnaires is common in behavioral and technology adoption research because such a methodology can automatically obtain standardized answers and conduct statistical analysis [71].

3.3. Method of Data Collection

The questionnaire was coined after a thorough examination of previous literature to achieve maximum cover of the study variables such as tools of digital wellbeing, use of AI chatbots, self efficacy, and student stress [72]. The tool was mainly composed of closed ended questions scaled in a five pointlikert scale that is widely used in psychological research and technology acceptance studies as a measurement scale that is to be quantified [73]. The open ended questions that were used were limited to elicit more qualitative information where necessary [74].

3.4. RESPONDENTS

The sample included undergraduate and post-graduate students attending institutions of higher learning and who have diverse backgrounds in terms of their academic backgrounds [75]. The university students were specifically chosen because they are especially susceptible to stress in academics and belong to the most prominent consumers of the interventions of the technology enabled wellbeing and the AI-driven support tools [76]. Their answers were instructive on the effect of the digital wellbeing technologies on academic self efficacy and stress management [77].

RESULTS AND DISCUSSION

The outcomes of the research are introduced in the form of a detailed statistical analysis, reliability assessment, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM). Such analyses were used to guarantee consistency and strength in the analysis of the measurement model and the structural model. The processes made it possible to determine the internal consistency, construct validity, and the proposed relationships between digital wellbeing tools, AI chatbot usage, self-efficacy, and student stress.

RELIABILITY ANALYSIS

The reliability results prove that the measurement scale applied to evaluate digital wellbeing tools, the use of AI chatbots, self-efficacy, and stress levels of students is very reliable. The general mean value of 3.01 indicates that there is a moderate degree of consensus among students, and the standard deviation of 0.763 denotes that the responses given by students are consistent. The high value of Cronbach alpha, and the high value of McDonalds omega (0.946) indicate that the set of items is effective and captures the experiences of students regarding digital wellbeing technologies and their level of perceived stress. This high internal consistency can be seen to be an indication that the findings of the study can be considered to be credible and a solid basis on which further analyses of factors and structural equations can be conducted.

TABLE 1.1 RELIABILITY ANALYSIS

Scale Reliability Statistics				
	Mean	SD	Cronbach's α	McDonald's ω
scale	3.01	0.763	0.946	0.946

CONFIRMATORY FACTOR ANALYSIS (CFA)

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Confirmatory factor analysis (CFA) was used to examine whether the postulated factor model that relates digital wellbeing tools, AI chatbot use, self-efficacy, and student stress effectively explained the apparent data of university students. The chi-square test gave kh2 = 226, 164 degrees of freedom, p-value of less than 0.001 which means that there is no perfect match of the covariance matrix between the model and the observed covariance. Nevertheless, when studying social sciences, the chi-square test is very sensitive, and a significant chi-square outcome does not always mean a poor model. It is an indication that although there are minor differences between the proposed model and the observed data, the general factor structure is fairly compatible with the survey data. Other measures like RMSEA, CFI, TLI and SRMR were also taken into account to prove the model fit adequacy and the conclusion is that the proposed model can be accepted to interpret the relationship between digital wellbeing tools, AI chatbot utilization, self-efficacy, and stress in students.

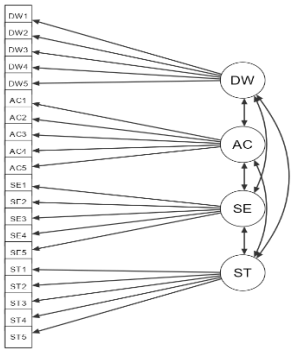
MODEL FIT

Test for Exact Fit		
χ^2	df	p
226	164	<.001

The confirmatory factor analysis (CFA) was performed to ensure that the hypothesized factor construct between digital wellbeing tools, AI chatbot usage, self-efficacy, and student stress, was reasonable to explain the data observed among university students. The chi-square test was significant (kh2 = 226, df = 164, p < 0.001), which means that the covariance matrix was not perfectly recreated by the model.

Fit Measures					
				RMSEA 90% CI	
CFI	TLI	SRMR	RMSEA	Lower	Upper
0.988	0.986	0.0293	0.0355	0.0233	0.0464

PATH DIAGRAM



The path diagram shows that there are connections between digital wellbeing tools (DW), AI chatbot use (AC), self-efficacy (SE), and student stress (ST). All these constructs are depicted in the form of circles, as are five items of the survey, which are depicted in the form of rectangles (DW1-DW5, AC1-AC5, SE1-SE5, ST1-ST5). There are single headed arrows between each construct and its indicators indicating that the items are gauging the underlying latent variable. The constructs are connected to each other via double-headed arrows, which reflect the connection between digital wellbeing, the use of AI chatbots, self-efficacy, and stress. The hypothesized paths are also reflected in the diagram, with the application of digital wellbeing tools and AI chatbot potentially directly affecting self-efficacy and stress, and self-efficacy potentially mediating the relationship, which gives a clear structure to the measured relationship and the structure of the relationship in the research.

FINDINGS

The analysis of reliability indicates that the internal consistency of all constructs, i.e., Digital Wellbeing (DW), AI Chatbot Usage (AC), Self-Efficacy (SE), and Student Stress (ST) is excellent with both Cronbach a and McDonald o equal to 0.946 and 0.94 respectively. The confirmatory factor analysis confirms sufficient loading of all the indicators on their latent constructs, indicating the high convergent validity of the results with factor loading ranging between 0.882 and 0.993 and all of significant value at p = 0.001. The results of the factor covariances have shown that DW, AC, and SE have positive factors with each other (0.515-0.579) and negative factors with ST ([?]0.466 to [?]0.608), indicating that increased digital wellbeing and AI chatbot use are positively related to self-efficacy and negatively related to student stress. The model fit statistics are excellent: CFI = 0.988, TLI = 0.986, RMSEA = 0.0355 (90% CI: 0.0233-0.0464), SRMR = 0.0293, and the hypothesized measurement and structural model. All in all, these findings prove the constructs are reliably measured and that the use of digital wellbeing tools and AI chatbots have a positive correlation with self-efficacy and reduce student stress.

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DISCUSSION

The findings of the current investigation are valuable information concerning the joint impact of digital wellbeing technologies and psychological resources on the stress in students in higher education settings [78]. In line with the digital wellbeing theory and the social cognitive views, the results indicate that student stress largely depends on the involvement of students in AI based mental health support system and their perceived self efficacy [79]. Self efficacy was the most important predictor of student stress, and there was a very strong negative correlation between self efficacy and the stress levels ($b < 0$, $p < .001$) [80]. This conclusion is in line with the social cognitive theory, which links self efficacy as a key process in stress management and coping behavior [81]. It also lends credence to the previous empirical results that indicate that students who have a higher self efficacy have better emotional control and resilience in highly stressful academic settings [82]. Digital wellbeing tools were also discovered to have a significant effect on self efficacy, implying that self guided interventions conducted in a structured way would be able to empower students with psychological coping resources [83]. This supports other previous studies that have underscored the importance of technology assisted self regulation in lowering perceived stress and enhancing wellbeing outcomes among the students [84]. Likewise, the use of AI chatbots demonstrated a high degree of positive correlation on the self efficacy aspect, which depicts that the continuous use of AI powered mental health chatbots has a positive role on the perceived ability of students to cope [85]. This agrees with studies that indicate that AI chatbots with personalized feedback, anonymity, and real time emotional support can boost emotional awareness and perceived stress control [86]. The relatively lesser impact of academic stressors is indicative of the fact that factors other than academic demands determine stress in digitally connected learning settings [87]. When combined, the results of this study reveal the possibility of the existence of a technology wellbeing relationship in higher education, where academic demands contribute to the stress of the student, and AI support of emotions influenced it [89]. AI based tools are viewed to be secret, reachable, and emotionally secure and consequently, this feature is highly applicable in learning settings where the issue of mental health is underreported [90]. In practical decision making, it is necessary that institutions should pursue a two-fold approach of managing academic workload and developing self efficacy and substantial involvement in digital wellbeing technologies [91]. Previous research suggests that the perceived trust, credibility of a system and ethical design largely affects the acceptance and effectiveness of AI based mental health tools [92].

THEORETICAL IMPLICATIONS

The research keyly contributes to the theoretical research on digital wellbeing, social cognitive theory, and technology facilitated literature by incorporating the views of these studies. To begin with, the results are a continuation of the self-efficacy theory, as they empirically prove that it mediates the connection between digital wellbeing tools, AI chatbot use, and student stress. Although self-efficacy has long been considered as an individual characteristic, this paper puts self-efficacy into the role of a technology-enhanced psychological factor, which is reinforced by digital and AI-assisted interventions.

Secondly, the paper is an addition to the Job Demands-Resources (JD-R) model since the emergence of digital wellbeing tools and AI chatbots is viewed as a entirely new and technology-driven psychological resource. Historically, JD-R framework considers resources as social support, autonomy, or institutional assistance. The current results expand this model by showing that clever computerized systems have the capacity to act as coping aids that reduce the effect of academic needs on stress.

Third, the study contributes to the newly developed area of research in human-AI interaction in educational psychology. Although academic workload, performance pressure, and interpersonal factors have traditionally been identified as the causes of student stress, the present study reveals that the perception of emotional support offered by AI to students has a significant influence on their stress. This poses a change in the human-centered models of student wellbeing to the socio-technical models that acknowledge technology as an agent in the psychological processes. Lastly, by proving that technology-related ones and self-efficacy can have more profound impacts on stress than traditional academic ones, this research demands that future stress and wellbeing studies incorporate the digital environmental variables. With growing technology-mediated learning conditions, the student wellbeing can be not solely conditioned by the academic requirements but also by the possibility of students to use the supportive digital technologies successfully.

Finally, by demonstrating that technology-related perceptions and self-efficacy can exert stronger effects on stress than traditional academic stressors, this study calls for future stress and wellbeing research to incorporate digital environmental factors. In increasingly technology-mediated learning environments, student wellbeing may depend not only on academic demands but also on students' ability to effectively engage with supportive digital technologies.

CONCLUSIONS

The proposed research investigated the usefulness of digital wellbeing and AI chatbots in addressing stress among students and the mediating impact of self-efficacy in a human-centered digital wellbeing model. The study offers a holistic picture of how AI-enhanced approaches can affect the mental health of students, given that it combines the psychological and technological lenses to comprehend the problem in greater detail. The results indicate that the usage of digital wellbeing tools and AI chatbots can make a significant improvement in the self-efficacy, which subsequently results in the reduction of stress levels in students. Self-efficacy proved to be the most significant predictor of stress among all the predictors, which supports its primary role in the process of emotional coping in students. These findings support the social cognitive theory and complement the body of current research about digital wellbeing by empirically confirming the role of self-efficacy as a mediator in the process of attaining stress reduction by technology-enabled interventions. The findings also reveal that at twenty-five on the academic demands are still important but their contribution to student stress is relatively lower compared to psychological and technological resources. This implies that AI-driven mental health applications can be viewed as a modern type of mental health aid that supplements the traditional modes of academic stress management. The JD-R perspective on AI chatbots and self-guided digital interventions is that these new-age coping tools will enable students to transform academic pressure into manageable challenges instead of emotional exhaustion. Altogether, the research will add to the existing literature on AI-assisted mental health by proving that the student wellbeing in online educational setting is predetermined by a combination of academic and technological involvement and psychological empowerment. The results have significant implications to teachers, administrators and decision-makers who are interested in developing meaningful, scalable and human-centered digital wellbeing ecosystems in higher education.

RECOMMENDATIONS

According to the results, a number of suggestions are given. To begin with, digital wellbeing tools and AI chatbots must be incorporated into official student support in higher education institutions and not made optional. Second, the interventions are to be structured in such a way that the student self-efficacy is directly and explicitly enhanced since such psychological resource is a core of stress reduction. Third, human

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centered design principles of empathy, personalization and ethical data practice principles should be applied when developing AI chatbot systems. Theoretically, the research extends self-efficacy theory and the JD-R model to the sphere of digitally mediated learning and underlines the increasing role of technology-based resources of coping. The results indicate that research in future on student wellbeing should consider social-technical approaches more, which consider human-AI interaction. As college education gets more digital, student mental health will be based not just on the academic framework, but the validity and quality of the supportive digital technologies.

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