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# Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students

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## Abstract

While the discussion on generative artificial intelligence, such as ChatGPT, is making waves in academia and the popular press, there is a need for more insight into the use of ChatGPT among students and the potential harmful or beneficial consequences associated with its usage. Using samples from two studies, the current research examined the causes and consequences of ChatGPT usage among university students. Study 1 developed and validated an eight-item scale to measure ChatGPT usage by conducting a survey among university students (N = 165). Study 2 used a three-wave time-lagged design to collect data from university students (N = 494) to further validate the scale and test the study's hypotheses. Study 2 also examined the effects of academic workload, academic time pressure, sensitivity to rewards, and sensitivity to quality on ChatGPT usage. Study 2 further examined the effects of ChatGPT usage on students' levels of procrastination, memory loss, and academic performance. Study 1 provided evidence for the validity and reliability of the ChatGPT usage scale. Furthermore, study 2 revealed that when students faced higher academic workload and time pressure, they were more likely to use ChatGPT. In contrast, students who were sensitive to rewards were less likely to use ChatGPT. Not surprisingly, use of ChatGPT was likely to develop tendencies for procrastination and memory loss and dampen the students' academic performance. Finally, academic workload, time pressure, and sensitivity to rewards had indirect effects on students' outcomes through ChatGPT usage.

**Keywords:** Workload, Time pressure, Sensitivity to quality, Sensitivity to rewards, ChatGPT usage, Procrastination, Memory loss, Academic performance

## Introduction

"The ChatGPT software is raising important questions for educators and researchers all around the world, with regards to fraud in general, and particularly plagiarism," a spokesperson for Sciences Po told Reuters (Reuters, 2023).

"I don't think it [ChatGPT] has anything to do with education, except undermining it. ChatGPT is basically high-tech plagiarism...and a way of avoiding learning," said Noam Chomsky, a public intellectual known for his work in modern linguistics, in an interview (EduKitchen & January21, 2023).

In recent years, the use of generative artificial intelligence (AI) has significantly influenced various aspects of higher education. Among these AI technologies, ChatGPT (OpenAI, 2022) has gained widespread popularity in academic settings for a variety of uses such as generation of codes or text, assistance in research, and the completion of assignments, essays and academic projects (Bahroun et al., 2023; Stojanov, 2023; Strzelecki, 2023). ChatGPT enables students to generate coherent and contextually appropriate responses to their queries, providing them with an effective resource for their academic work. However, the extensive use of ChatGPT brings a number of challenges for higher education (Bahroun et al., 2023; Chan, 2023; Chaudhry et al., 2023; Dalalah & Dalalah, 2023).

Scholars have speculated that the use of ChatGPT may bring many harmful consequences for students (Chan, 2023; Dalalah & Dalalah, 2023; Dwivedi et al., 2023; Lee, 2023). It has the potential to harmfully affect students' learning and success (Korn & Kelly, 2023; Novak, 2023) and erode their academic integrity (Chaudhry et al., 2023). Such lack of academic integrity can damage the credibility of higher education institutions (Macfarlane et al., 2014) and harm the achievement motivation of students (Krou et al., 2021). However, despite the increasing usage of ChatGPT in higher education, very rare empirical research has focused on the factors that drive its usage among university students (Strzelecki, 2023). In fact, majority of the prior studies consist of theoretical discussions, commentaries, interviews, reviews, or editorials on the use of ChatGPT in academia (e.g., Cooper, 2023; Cotton et al., 2023; Dwivedi et al., 2023; King, 2023; Peters et al., 2023). For example, we have a very limited understanding of the key drivers behind the use of ChatGPT by university students and how ChatGPT usage affects their personal and academic outcomes. Similarly, despite many speculations, very limited research has empirically examined the beneficial or harmful effects of generative AI usage on students' academic and personal outcomes (e.g., Yilmaz & Yilmaz, 2023a, 2023b). Even these studies provide contradictory evidence on whether ChatGPT is helpful or harmful for students.

Therefore, an understanding of the dynamics and the role of generative AI, such as ChatGPT, in higher education is still in its nascent stages (Carless et al., 2023; Strzelecki, 2023; Yilmaz & Yilmaz, 2023a). Such an understanding of the motives behind ChatGPT usage and its potentially harmful or beneficial consequences is critical for educators, policymakers, and students, as it can help the development of effective strategies to integrate generative AI technologies into the learning process and control their misuse in higher education (Meyer et al., 2023). For the same reasons, scholars have called for future research to delve deeper into the positives and negatives of ChatGPT in higher education (Bahroun et al., 2023; Chaudhry et al., 2023; Dalalah & Dalalah, 2023).

Taken together, the current study has several objectives that aim to bridge these gaps and significantly contribute to the body of knowledge and practice in higher education. First, responding to the call of prior research on the development of ChatGPT usage scale (Paul et al., 2023), we develop and validate a scale for ChatGPT usage in study 1. Next, we conduct another study (i.e., study 2) to investigate several theoretically relevant factors—such as academic workload, time pressure, sensitivity to rewards, and sensitivity to quality—which may potentially affect the use of ChatGPT by university students. In addition, concerns have been raised regarding the impact of ChatGPT on

students' academic performance and creativity. For example, scholars consider the use of ChatGPT as "deeply harmful to a social understanding of knowledge and learning" (Peters et al., 2023, p. 142) and having the potential to "kill creativity and critical thinking" (Dwivedi et al., 2023, p. 25). However, empirical evidence regarding the harmful or beneficial consequences of ChatGPT usage remains largely unavailable. Therefore, we investigate the effects of ChatGPT usage on students' procrastination, memory retention/loss, and academic performance (i.e., CGPA). Together, this research aims to provide valuable insights for educators, policymakers, and students in understanding the factors that encourage the use of ChatGPT by students and the beneficial or deleterious effects of such usage in higher education.

## **Literature and hypotheses**

### ***Academic workload and use of ChatGPT***

Academic workload refers to the number of academic tasks, responsibilities, and activities that students are required to complete during a specific period, usually a semester. The workload encompasses the volume and complexity of assignments or projects (Bowyer, 2012). Students are put under high stress when they have an excessive amount of academic work to complete (Yang et al., 2021).

Studies indicate that overburdened students are more likely to rely on unethical means to complete their academic tasks instead of relying on their own abilities and learning. For example, Devlin and Gray (2007) found that students engage in unethical academic practices such as cheating and plagiarism when they are exposed to heavy workload. Similarly, Koudela-Hamila et al. (2022) found a significantly positive relationship between academic workload and academic stress among university students. In another study, Hasebrook et al. (2023) found that individuals were more likely to accept and adopt technology when their workload was high. Consistently, when students are faced with high workload, they look for ways to cope with this demanding situation. As a result, they use easy means or shortcuts (e.g., ChatGPT) to cope with such stressful situations (i.e., heavy workload). Consequently, we suggest:

*Hypothesis 1* Workload will be positively related to the use of ChatGPT.

### ***Time pressure and use of ChatGPT***

Time pressure is described as the perception that an impending deadline is becoming closer and closer (Carnevale & Lawler, 1986). Under time pressure, individuals use simple heuristics in order to complete tasks (Rieskamp & Hoffrage, 2008). Under high time pressure, students may consider the available time as insufficient to accomplish the assignments, and therefore they may rely on ChatGPT to complete these tasks. Preliminary research indicates that time pressure to complete academic tasks encourages plagiarism among students (Koh et al., 2011). Devlin and Gray (2007) also found that students engage in cheating and plagiarism under time pressure to complete their academic tasks. Similarly, those students who are exposed to time pressure adopt a surface learning approach (Guo, 2011), which indicates that the students may use shortcuts such as ChatGPT to complete their tasks within deadlines. Therefore, we argue that under

high levels of time pressure, students are more likely to use ChatGPT for their academic activities. Consequently, we suggest:

*Hypothesis 2* Time pressure will be positively related to the use of ChatGPT.

#### ***Sensitivity to rewards and use of ChatGPT***

Sensitivity to rewards is the degree to which a student is worried or concerned about his or her academic rewards such as grades. As far as the relationship between sensitivity to rewards and ChatGPT usage is concerned, prior research does not help to make a clear prediction. For example, on the one hand, it is possible that students with higher sensitivity to rewards may be more inclined to use ChatGPT, as they perceive it as a means to obtain better academic results. They may see ChatGPT as a resource to enhance their academic performance and get good grades. Evidence indicates that individuals, who are highly sensitive to rewards or impulsive, have a tendency to engage in risky behaviors such as texting on their cell phones while driving (Hayashi et al., 2015; Pearson et al., 2013). This indicates that students, who are reward sensitive, may engage in risky behaviors such as the misuse of ChatGPT for academic activities or plagiarism.

On the other hand, it is also possible that students who are highly worried about their rewards may not use ChatGPT for the fear of losing their grades. Since the use of ChatGPT for academic activities is usually considered as an unethical mean (Dalalah et al., 2023; Dwivedi et al., 2023), highly reward sensitive individuals may be more cautious about using technologies that their teachers perceive as ethically questionable or could jeopardize their academic integrity and grades. Consequently, we suggest competing hypotheses:

*Hypothesis 3a* Sensitivity to rewards will be positively related to the use of ChatGPT.

*Hypothesis 3b* Sensitivity to rewards will be negatively related to the use of ChatGPT.

#### ***Sensitivity to quality and use of ChatGPT***

Sensitivity to quality or quality consciousness refers to the extent to which students are perceptive when evaluating the standard and excellence of their educational activities. This sensitivity involves the students' consciousness of the quality of learning they are having (Olugbara et al., 2020) or the quality of contents (e.g., assignments or projects) they are working on. We suggest that students, who are sensitive to the quality of the contents, are more likely to use different tools to enhance the quality of their academic work.

ChatGPT can be used by quality-conscious students for numerous reasons. Students, who are sensitive to quality, may want to ensure excellence, accuracy, and reliability in their work—and they may recognize the potential benefits of using ChatGPT to meet their expectations for high-quality academic work (Haensch et al., 2023; Yan, 2023). Similarly, students high in sensitivity to quality often pay great attention to grammar, style, and language precision. ChatGPT can assist in refining their written work by providing suggestions for sentence structure, word choice, and grammar (Abbas, 2023; Dwivedi et al., 2023). Therefore, students with a strong sensitivity to quality are more likely to

use ChatGPT in order to enhance the quality of their academic work (e.g., assignments, projects, essays, or presentations), as compared to those who are not sensitive to quality. Consequently, we suggest:

*Hypothesis 4* Sensitivity to quality will be positively related to the use of ChatGPT.

#### ***Use of ChatGPT and procrastination***

Procrastination occurs when people “voluntarily delay an intended course of action despite expecting to be worse off for the delay” (Steel, 2007, p. 66). Some individuals are predisposed to put off doing things until later (i.e., chronic procrastinators), whereas others only do so in certain circumstances (Rozental et al., 2022). Academic procrastination, which refers to the practice of routinely putting off academic responsibilities to the point that the delays become damaging to performance, is an important issue both for students and educational institutions (Svartdal & Løkke, 2022).

Studies suggest that procrastination occurs very frequently in students (Bäulke & Dresel, 2023) and it may be influenced by a variety of environmental and personal factors (Liu et al., 2023; Steel, 2007). We argue that the use of generative AI may influence the tendencies for procrastination among students. Using short-cuts, which may help students to complete the academic tasks without putting much efforts, will eventually make the students habitual. As a result, these short cuts—such as the use of ChatGPT—may cause procrastination among students. For example, a student who is addicted to ChatGPT usage may believe that he or she can complete an academic assignment or a project within less time and without putting much efforts. Such feelings of having control over the tasks are likely to encourage the students to delay those tasks till the last moment, thereby resulting in procrastination. More recent evidence also indicates that ChatGPT usage may cause laziness among students (Yilmaz & Yilmaz, 2023a). Consequently, we suggest:

*Hypothesis 5* Use of ChatGPT will be positively related to procrastination.

#### ***Use of ChatGPT and memory loss***

Memory loss refers to a condition or a state in which an individual experiences difficulty in recalling information or events from the past (Mateos et al., 2016). Scholars indicate that cognitive, emotional, or physical conditions affect memory functioning among individuals (Fortier-Brochu et al., 2012; Schweizer et al., 2018). We argue that excessive use of ChatGPT may result in memory loss among students. Continuous use of ChatGPT for academic tasks may develop laziness among the students and weaken their cognitive skills (Yilmaz & Yilmaz, 2023a) leading to a memory loss.

Over time, overreliance on generative AI tools for academic tasks, instead of critical thinking and mental exertion, may damage memory retention, cognitive functioning, and critical thinking abilities (Bahrini et al., 2023; Dwivedi et al., 2023). Active learning, which involves active cognitive engagement with the content, is crucial for memory consolidation and retention (Cowan et al., 2021). Since ChatGPT can quickly respond to any questions asked by a user (Chan et al., 2023), students who excessively use ChatGPT

may reduce their cognitive efforts to complete their academic tasks, resulting in poor memory.

Related evidence demonstrates that daily mental training helps to improve cognitive functions among individuals (Uchida & Kawashima, 2008). Similarly, fast simple numerical calculation training (FSNC) was associated with improvements in performance on simple processing speed, improved executive functioning, and better performance in complex arithmetic tasks (Takeuchi et al., 2016). Moreover, Nouchi et al. (2013) found that brain training games helped to boost working memory and processing speed in young adults. Therefore, the extensive use of ChatGPT may yield an absence of such cognitive trainings, thereby leading to memory loss among students. Consequently, we suggest:

*Hypothesis 6* Use of ChatGPT will be positively related to memory loss.

#### ***Use of ChatGPT and academic performance***

Academic performance refers to the level of accomplishment that a student demonstrates in his or her educational pursuits. The objective measure of a student's academic performance is indicated by cumulative grade point average (CGPA), which is a grading system used in educational institutions to measure a student's overall academic performance in a specific period, usually a semester.

If students effectively leverage the insights gained from ChatGPT to improve their understanding of a subject, it may positively influence their academic performance. However, if they rely solely on ChatGPT without putting in the necessary efforts, critical thinking, and independent study, it may harm their academic performance. Over-reliance on external sources, including generative AI tools, without personal engagement and active learning, can hinder the development of essential skills and the depth of knowledge required for academic success (Chan et al., 2023). Therefore, students who habitually use ChatGPT may end up demonstrating poor academic performance. Consequently, we suggest:

*Hypothesis 7* Use of ChatGPT will be negatively related to academic performance.

#### ***The mediating role of ChatGPT usage***

We further suggest that ChatGPT usage will mediate the relationships of workload, time pressure, sensitivity to quality, and sensitivity to rewards with students' outcomes. Specifically, students who experience heavy workload and time pressure to complete their academic tasks are likely to engage in ChatGPT usage to cope with these stressful situations. In turn, reliance on ChatGPT may lead to delays in the accomplishment of the tasks (i.e., procrastination) because the students may believe that they can complete the tasks at any time without putting much efforts. Similarly, the excessively reliance on ChatGPT, as a substitute for their critical thinking and problem-solving skills, may hinder their ability to develop a deeper understanding of the subject matter, which can harmfully impact their academic performance (Abbas, 2023). Further, the high use of ChatGPT for academic tasks could potentially lead to reduced mental engagement,

thereby exacerbating the risk of memory impairment (Bahrini et al., 2023; Dwivedi et al., 2023).

Moreover, ChatGPT usage will mediate the relationships of rewards sensitivity and quality sensitivity with procrastination, memory loss, and academic performance. The fear of losing marks (i.e., reward sensitivity) and the consciousness towards quality of academic work (i.e., sensitivity to quality), may influence the use of ChatGPT. In turn, the excessive (or less) use of ChatGPT may affect students' procrastination, memory loss, and academic performance. Together, we suggest:

*Hypothesis 8* Use of ChatGPT will mediate the relationships of workload with procrastination, memory loss, and academic performance.

*Hypothesis 9* Use of ChatGPT will mediate the relationships of time pressure with procrastination, memory loss, and academic performance.

*Hypothesis 10* Use of ChatGPT will mediate the relationships of sensitivity to rewards with procrastination, memory loss, and academic performance.

*Hypothesis 11* Use of ChatGPT will mediate the relationships of sensitivity to quality with procrastination, memory loss, and academic performance.

## **Methods (Study 1)**

### ***ChatGPT usage scale development procedures***

*Item generation:* We used scale development procedures proposed in prior research (Hinkin, 1998). We first defined ChatGPT usage as the extent to which students use ChatGPT for various academic purposes including completion of assignments, projects, or preparation of exams. Based on this definition, initially 12 items were developed for further scrutiny.

*Initial item reduction:* Following the guidelines of Hinkin (1998), we performed an item-sorting process during the early stages of scale development. In order to establish content validity of the ChatGPT usage scale, we conducted interviews from five experts of the relevant field. The experts were asked to evaluate each item intended to measure ChatGPT usage. The experts agreed that 10 of the 12 items measured certain aspects of the academic use of ChatGPT by the students. Based on the content validity, these 10 items were finalized for further analyses.

### ***Sample and data collection***

The 10-item scale for the use of ChatGPT was distributed among 165 students from numerous university across Pakistan. The responses were taken on a 6-point Likert type scale with anchors ranging from 1 = never to 6 = always. A cover letter clearly communicated that the participation was voluntary, and the student could decline participation at any point during data collection. The respondents were also ensured complete confidentiality of their responses. The sample consisted of 53.3% males. The average age was 23.25 year (S.D = 4.22). Around 85% universities were from public sector and the remaining belonged to private sector. Similarly, around 59% students

were enrolled in business studies, 6% were enrolled in computer sciences, 9% were enrolled in general education, 5% were enrolled in psychology, 4% were enrolled in English language, 4% were enrolled in public administration, 9% were enrolled in sociology, and 4% were enrolled in mathematics. Furthermore, around 74% were enrolled in bachelor’s programs, 22% were enrolled in master’s programs, and 4% were enrolled in doctoral programs.

**Exploratory factor analysis**

Next, we conducted an exploratory factor analysis (EFA) to determine the factor structure of the proposed scale (Field, 2018; Hinkin, 1998). Principal component analysis (Nunnally & Bernstein, 1994) was used for extraction and the varimax rotation with Kaiser normalization was used as a rotation method. To ascertain the number of variables, the parameters of eigenvalue > 1 and the total percentage of variance explained > 50% were used. The results revealed that the Bartlett’s test of sphericity was significant ( $p < 0.001$ ) and the Kaiser–Meyer–Olkin (KMO) sampling adequacy was 0.878 ( $p < 0.001$ ), which was greater than the threshold value of 0.50, thereby considered acceptable for sample adequacy (Field, 2018). Further, factor loadings and communalities above 0.5 are usually considered acceptable (Field, 2018). As shown in Table 1, the results revealed that item 4 and item 9 had low factor loadings and communalities.

We then dropped these two items and conducted another EFA on the remaining eight items. As presented in Table 2, all 8 items exceeded the threshold criteria. Also, a one-factor structure accounted for 62.65% of the cumulative variance with all item loadings above 0.50. Therefore, the final scale to measure use of ChatGPT consisted of eight items. The Cronbach’s alpha (CA) for the 8-item scale was  $\alpha = 0.914$  and the composite reliability (CR) was 0.928. These scores of CA and CR exceeded the threshold value of 0.7, thereby indicating construct reliability (Nunnally & Bernstein, 1994). Finally, as shown in Table 2, the average variance extracted (AVE) score was 0.618, which was above the threshold value of 0.5, thus indicating convergent validity (Hair et al., 2019). Together, these results established good reliability and validity of the 8-item scale to measure ChatGPT usage.

**Table 1** Use of ChatGPT scale: factor loadings, communalities, and total variance extracted (Study 1)

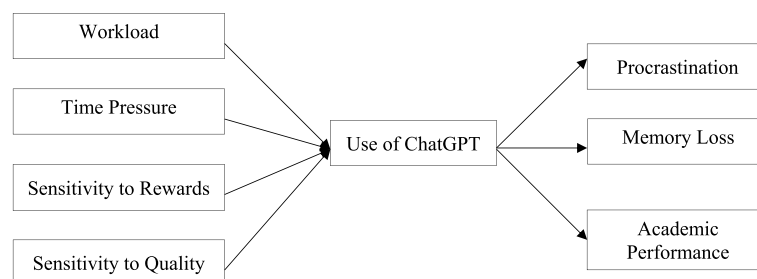
Items	Factor loading	Communalities	Total variance extracted
I use ChatGPT for my course assignments	0.82	0.67	54.721
I use ChatGPT for my course projects	0.78	0.60	
I use ChatGPT for my academic activities	0.82	0.67	
I can’t think of studies without ChatGPT	0.58	0.34	
I rely on ChatGPT for my studies	0.79	0.63	
I use ChatGPT to learn course-related concepts	0.76	0.57	
I am addicted to ChatGPT when it comes to studies	0.79	0.63	
I use ChatGPT to prepare for my tests or quizzes	0.76	0.58	
Use of ChatGPT is common nowadays	0.44	0.19	
ChatGPT is part of my campus life	0.77	0.59	



**Table 2** Revised use of ChatGPT scale: factor loadings, communalities, and total variance extracted (Study 1)

Items	Factor loading	Communalities	Total variance extracted	CA	CR	AVE
I use ChatGPT for my course assignments	0.837	0.701	62.650	0.914	0.928	0.618
I use ChatGPT for my academic activities	0.824	0.680				
I use ChatGPT for my course projects	0.798	0.637				
I am addicted to ChatGPT when it comes to studies	0.792	0.627				
I rely on ChatGPT for my studies	0.780	0.608				
I use ChatGPT to prepare for my tests or quizzes	0.775	0.601				
I use ChatGPT to learn course-related concepts	0.769	0.592				
ChatGPT is part of my campus life	0.752	0.566				

CA Cronbach's Alpha, CR composite reliability, AVE average variance extracted



**Fig. 1** Theoretical framework of the study

**Methods (Study 2)**

**Sample and data collection procedures**

The objective of study 2 was to further validate the 8-item ChatGPT scale developed in study 1. In addition, we tested the study’s hypotheses in study 2. Figure 1 presents the theoretical framework of study 2. The study used a time-lagged design, whereby the data were collected using online forms in three phases with a gap of 1–2 weeks after each phase. The data were collected from individuals who were currently enrolled in a university.

We used procedural and methodological remedies recommended by scholars (see, Podsakoff et al., 2012) to address issues related to common method bias. First, we clearly communicated to our participants that their involvement was voluntary, and they retained the right to decline participation at any point during data collection. In addition, we ensured complete confidentiality of their responses, emphasizing that there were no right or wrong responses to the questions. Finally, we used a three-wave time-lagged design to keep a temporal separation between predictors and outcomes (Podsakoff et al., 2012). In each phase, the students were asked to assigned a code initially generated by them so that the survey forms for each respondent could be matched. Moreover, ethical clearance and approvals from the ethics committees of the authors’ institutions were

also obtained. Since English is the official language in all educational institutions, the survey forms were distributed in English. Past research has also used English language for survey research (e.g., Abbas & Bashir, 2020; Fatima et al., 2023; Malik et al., 2023).

In the first phase, around 900 participants were contacted to fill the survey on workload, time pressure, sensitivity to quality, sensitivity to rewards, and demographics. At the end of the first phase, a total of 840 surveys were received. In the second phase, after 1–2 weeks, the same respondents were contacted to fill the survey on the use of ChatGPT. Around 675 responses were received at the end of the second phase. Finally, another two weeks later, these 675 respondents were contacted again to collect data on memory loss, procrastination, and academic performance. At the end of the third phase, around 540 survey forms were returned. After removing surveys which contained missing data, the final sample size consisted of 494 complete responses which were then used for further analyses.

Of these 494 respondents, 50.8% were males and the average age of the respondents was 22.16 (S.D. = 3.47) years. Similarly, 88% of the respondents belonged to public sector and 12% belonged to private sector universities. Around 65% students were enrolled in business studies, 3% were enrolled in computer sciences, 12% were enrolled in general education, 1% were studying English language, 9% were studying public administration, and 10% were studying sociology. Finally, around 74% were enrolled in bachelor's programs, 24% were enrolled in master's programs, and 2% were enrolled in doctoral programs.

### Measures

All variables, except for the use of ChatGPT, were measured on a 5-point Likert type scale with anchors ranging from 1 = strongly disagree to 5 = strongly agree. Use of ChatGPT was measured on a 6-point Likert type scale with anchors ranging from 1 = never to 6 = always. The complete items for all measures are presented in Table 3.

*Academic workload:* A 4-item scale by Peterson et al. (1995) was adapted to measure academic workload. A sample item included, 'I feel overburdened due to my studies.'

*Academic time pressure:* A 4-item scale by Dapkus (1985) was adapted to measure time pressure. A sample item was, 'I don't have enough time to prepare for my class projects.'

*Sensitivity to rewards:* We measured sensitivity to rewards with a 2-item scale. The items included, 'I am worried about my CGPA' and 'I am concerned about my semester grades.'

*Sensitivity to quality:* Sensitivity to quality was measured with a 2-item scale. The items were, 'I am sensitive about the quality of my course assignments' and 'I am concerned about the quality of my course projects.'

*Use of ChatGPT:* We used the 8-item scale developed in study 1 to measure the use of ChatGPT. A sample item was, 'I use ChatGPT for my academic activities.'

*Procrastination:* A 4-item scale developed by Choi and Moran (2009) was used to measure procrastination. A sample item included, 'I'm often running late when getting things done.'

*Memory loss:* We used a 3-item scale to measure memory loss. A sample item was, 'Nowadays, I can't retain too much in my mind.'

**Table 3** Factor loading, reliability, and validity (Study 2)

Items	Loadings	CA	CR	AVE
<i>Workload</i> (Peterson et al., 1995)		0.845	0.895	0.680
My academic workload is too heavy	0.861			
I feel overloaded by the work my studies require	0.838			
I feel overburdened due to my studies	0.810			
The teacher(s) give too much work to do	0.788			
<i>Time pressure</i> (Dapkus, 1985)		0.740	0.833	0.562
I don't have enough time to prepare for my class projects	0.829			
I don't have enough time to complete study-related tasks with appropriate care	0.810			
I find it difficult to submit my assignments and projects within the deadlines	0.804			
I am often in hurry when it comes to meeting academic deadlines	0.511			
<i>Sensitivity to rewards</i>		0.881	0.944	0.894
I am worried about my CGPA	0.947			
I am concerned about my semester grades	0.944			
<i>Sensitivity to quality</i>		0.717	0.871	0.773
I am concerned about the quality of my course projects	0.930			
I am sensitive about the quality of my course assignments	0.825			
<i>Use of ChatGPT</i>		0.903	0.922	0.596
I use ChatGPT for my academic activities	0.812			
I use ChatGPT to prepare for my tests or quizzes	0.795			
I use ChatGPT for my course projects	0.788			
I use ChatGPT to learn course-related concepts	0.778			
I rely on ChatGPT for my studies	0.771			
I use ChatGPT for my course assignments	0.762			
I am addicted to ChatGPT when it comes to studies	0.735			
ChatGPT is part of my campus life	0.732			
<i>Procrastination</i> (Choi & Moran, 2009)		0.756	0.845	0.577
I often fail to accomplish goals that I set for myself	0.795			
I'm often running late when getting things done	0.792			
I often start things at the last minute and find it difficult to complete them on time	0.739			
I have difficulty finishing activities once I start them	0.710			
<i>Memory loss</i>		0.757	0.860	0.672
Nowadays, I often forget things to do	0.862			
Nowadays, I can't retain too much in my mind	0.829			
Nowadays, I feel that I am losing my memory	0.765			

The CA, CR, and AVE for academic performance was not calculated because it was measured using a single item/score (i.e., CGPA)

CA Cronbach's Alpha, CR composite reliability, AVE average variance extracted

*Academic performance:* We used an objective measure of academic performance to avoid self-report or social desirability bias. Each student reported his or her latest CGPA. The CGPA score ranges between 1 = lowest to 4 = highest. Since CGPA for each respondent was obtained as a single score, there was no need to calculate its reliability or validity.

### Analyses and results (Study 2)

We used partial least squares (PLS) method to validate the measurements and test the hypotheses, as PLS is a second-generation structural equation modeling (SEM) technique that estimates relationships among latent variables by taking measurement errors into account and it is considered as a superior technique (Hair et al., 2017). The program utilizes bootstrapping approaches which entails the process of resampling from the dataset to provide standard errors and confidence intervals, yielding a more precise assessment of the model's stability (Hair et al., 2017, 2019). Further, partial least squares (PLS) are often favored in situations with limited sample numbers and non-normal distributions (Hair et al., 2019).

#### Measurement model

The measurement model is presented in Fig. 2. In the measurement model, first, we ran all the constructs together and examined the commonly used indicators of standardized factor loading, CA, CR, and AVE. The measurement model exhibited adequate levels of validity and reliability. As shown in Table 3, the standardized factor loadings for each item of each measure were above the threshold level of 0.70 (Hair et al., 2019). Similarly, CA and CR scores for each measure were above 0.70 and the AVE also surpassed 0.5. All scores exceeded the cut-off criteria, thereby establishing reliability and convergent validity of each construct (Hair et al., 2019).

Furthermore, discriminant validity ensures that each latent construct is distinct from other constructs. As per Fornell and Larcker's (1981) criteria, discriminant validity is established if the squared root of the AVE for each construct is larger than the correlation of that construct with other constructs. As shown in Table 4, the squared root of the AVE for each construct (the value along the diagonal presented in bold) exceeded

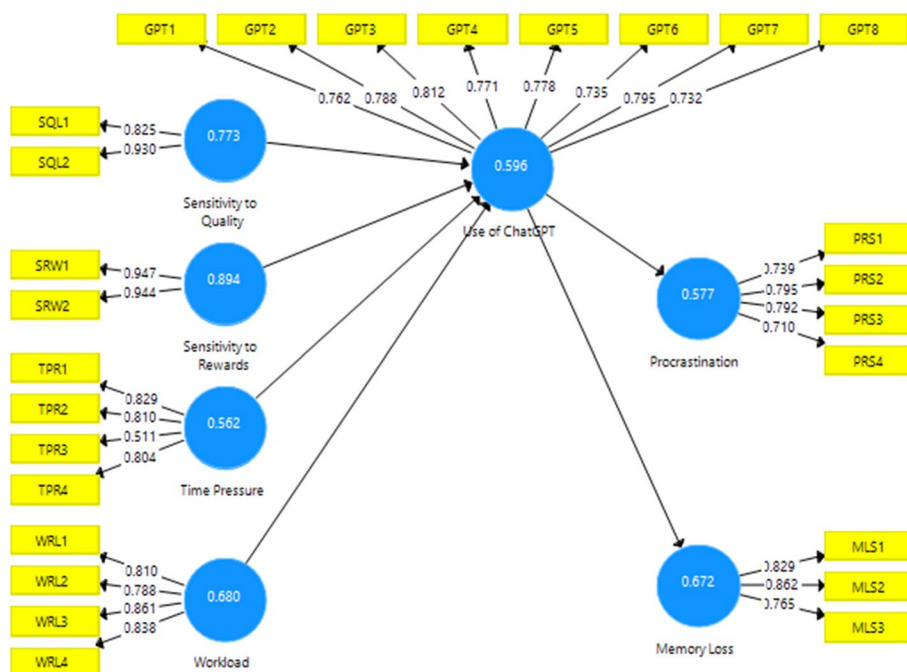


Fig. 2 Measurement indicators outer-loadings and AVE (Study 2)

**Table 4** Discriminant validity (Study 2)

	Fornell and Larcker criteria						Heterotrait-monotrait ratio							
	1	2	3	4	5	6	7	1	2	3	4	5	6	
1. Workload	<b>0.825</b>													
2. Time pressure	0.560	<b>0.750</b>						0.695						
3. Sensitivity to rewards	0.174	0.051	<b>0.945</b>					0.208	0.072					
4. Sensitivity to quality	0.266	0.104	0.489	<b>0.879</b>				0.346	0.161	0.611				
5. Use of ChatGPT	0.216	0.236	-0.051	0.038	<b>0.772</b>			0.233	0.266	0.088	0.086			
6. Procrastination	0.276	0.366	0.062	0.050	0.307	<b>0.760</b>		0.336	0.493	0.075	0.089	0.361		
7. Memory loss	0.278	0.246	0.111	0.053	0.273	0.551	<b>0.820</b>	0.345	0.334	0.139	0.084	0.322	0.724	

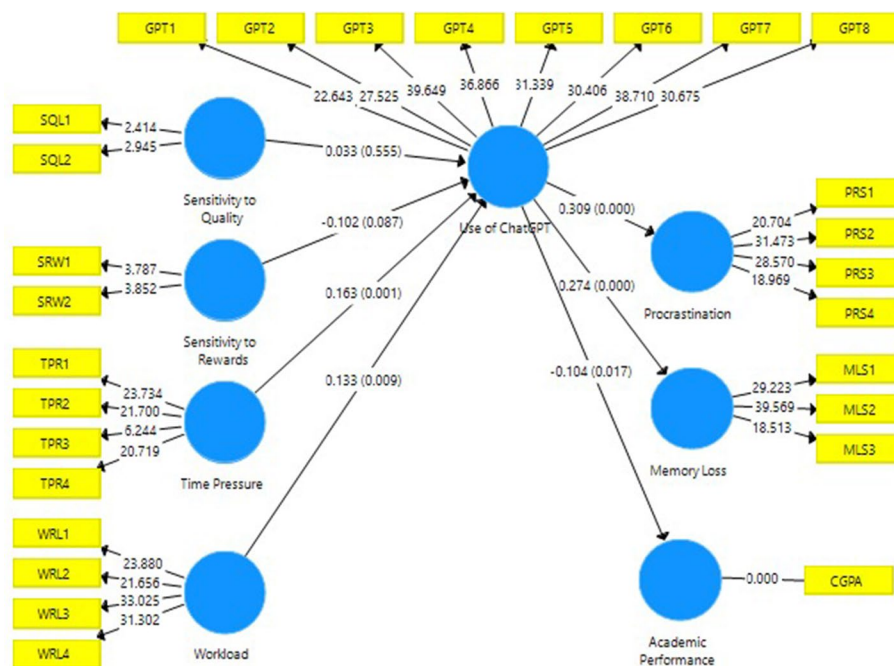
the correlation of that construct with other constructs, thereby establishing discriminant validity of all constructs. Similarly, Henseler et al. (2015) consider Heterotrait-Monotrait (HTMT) ratio as a better tool to establish discriminant validity, as a large number of researchers have also used it (e.g., Hosta & Zabkar, 2021). HTMT values below 0.85 are considered good to establish discriminant validity (Henseler et al., 2015). As shown in Table 4, all of the HTMT values were below the threshold, thereby establishing discriminant validity among the study’s constructs.

Furthermore, in order to test multicollinearity, we calculated variance inflation factor (VIF), which should be less than 5 to rule out the possibility of multicollinearity among the constructs (Hair et al., 2019). In all analyses, VIF scores were less than 5, indicating that multicollinearity was not a problem.

**Structural model**

We then tested the study’s hypotheses for direct and indirect effect using bootstrapping procedures with 5,000 samples in SmartPLS (Hair et al., 2017). The structural model is presented in Fig. 3.

As presented in Table 5, the findings revealed that workload was positively related to the use of ChatGPT ( $\beta=0.133, t=2.622, p<0.01$ ). Those students who experienced high levels of academic workload were more likely to engage in ChatGPT usage. This result supported hypothesis 1. Similarly, time pressure also had a significantly positive relationship with the use of ChatGPT ( $\beta=0.163, t=3.226, p<0.001$ ), thereby supporting hypothesis 2. In other words, students who experienced high time pressure to accomplish their academic tasks also reported higher use of ChatGPT. Further, the effect of sensitivity to rewards on the use of ChatGPT was negative and marginally significant ( $\beta= - 0.102, t= 1.710, p<0.10$ ), thereby suggesting that students who are more sensitive



**Fig. 3** Structural model (Study 2)

**Table 5** Direct effects (Study 2)

Hypothesis	Path	Coefficient	T Statistics	P-value	Status
H1	Workload -> Use of ChatGPT	0.133	2.622	0.009	Supported
H2	Time Pressure -> Use of ChatGPT	0.163	3.226	0.001	Supported
H3a, H3b	Sensitivity to Rewards -> Use of ChatGPT	- 0.102	1.710	0.087	H3b supported
H4	Sensitivity to Quality -> Use of ChatGPT	0.033	0.590	0.555	Not supported
H5	Use of ChatGPT -> Procrastination	0.309	6.984	0.000	Supported
H6	Use of ChatGPT -> Memory Loss	0.274	6.452	0.000	Supported
H7	Use of ChatGPT -> Academic Performance	- 0.104	2.390	0.017	Supported

to rewards are less likely to use ChatGPT. These results supported hypothesis 3b instead of hypothesis 3a. Finally, we found that sensitivity to quality was not significantly related to the use of ChatGPT ( $\beta=0.033, t=0.590, n.s$ ). Thus, hypothesis 4 was not supported.

Consistent with hypothesis 5, the findings further revealed that the use of ChatGPT was positively related to procrastination ( $\beta=0.309, t=6.984, p<0.001$ ). Those students who frequently used ChatGPT were more likely to engage in procrastination than those who rarely used ChatGPT. Use of ChatGPT was also found to be positively related to memory loss ( $\beta=0.274, t=6.452, p<0.001$ ), thus hypothesis 6 was also supported. Students who frequently used ChatGPT also reported memory impairment. Furthermore, use of ChatGPT was found to have a negative effect on academic performance (i.e., CGPA) of the students ( $\beta=-0.104, t=2.390, p<0.05$ ). Students who frequently used ChatGPT for their academic tasks had poor CGPAs. These findings rendered support for hypothesis 7.

Table 6 presents the results for all indirect effects. As shown in Table 6, workload had a positive indirect effect on procrastination (indirect effect=0.041,  $t=2.384, p<0.05$ ) and memory loss (indirect effect=0.036,  $t=2.333, p<0.05$ ) through the use of ChatGPT. Students who experienced higher workload were more likely to use ChatGPT which in turn developed the habits of procrastination among them and caused memory loss. Similarly, workload had a negative indirect effect on academic performance (indirect effect = - 0.014,  $t=1.657, p<0.10$ ) through the use of ChatGPT. In other words, students who experienced higher workload were more likely to use ChatGPT. As a result, the extensive use of ChatGPT dampened their academic performance. These results supported hypothesis 8.

In addition, time pressure had a positive indirect effect on both procrastination (indirect effect=0.050,  $t=2.607, p<0.01$ ) and memory loss (indirect effect=0.045,  $t=2.574, p<0.01$ ), through an increased utilization of ChatGPT. Students facing higher time constraints were more inclined to use ChatGPT, ultimately fostering procrastination habits and experiencing memory issues. Similarly, time pressure had a negative indirect effect on academic performance (indirect effect = - 0.017,  $t=1.680, p<0.10$ ), mediated by the increased use of ChatGPT. Thus, students experiencing greater time pressure were more likely to rely heavily on ChatGPT, consequently leading to a dampening of their academic performance. Together, these results supported hypothesis 9.

Furthermore, sensitivity to rewards had a negative indirect relationship with procrastination (indirect effect = - 0.032,  $t=1.676, p<0.10$ ) and memory loss (indirect

**Table 6** Indirect effects via use of ChatGPT (Study 2)

Hypothesis	Path	Coefficient	T Statistics	P-value	Status
H8	Workload -> Use of ChatGPT -> Procrastination	0.041	2.384	0.017	Supported
H8	Workload -> Use of ChatGPT -> Memory Loss	0.036	2.333	0.020	Supported
H8	Workload -> Use of ChatGPT -> Academic Performance	- 0.014	1.657	0.098	Supported
H9	Time Pressure -> Use of ChatGPT -> Procrastination	0.050	2.607	0.009	Supported
H9	Time Pressure -> Use of ChatGPT -> Memory Loss	0.045	2.574	0.010	Supported
H9	Time Pressure -> Use of ChatGPT -> Academic Performance	- 0.017	1.680	0.093	Supported
H10	Sensitivity to Rewards -> Use of ChatGPT -> Procrastination	- 0.032	1.676	0.094	Supported
H10	Sensitivity to Rewards -> Use of ChatGPT -> Memory Loss	- 0.028	1.668	0.095	Supported
H10	Sensitivity to Rewards -> Use of ChatGPT -> Academic Performance	0.011	1.380	0.168	Not supported
H11	Sensitivity to Quality -> Use of ChatGPT -> Procrastination	0.010	0.582	0.561	Not supported
H11	Sensitivity to Quality -> Use of ChatGPT -> Memory Loss	0.009	0.582	0.561	Not supported
H11	Sensitivity to Quality -> Use of ChatGPT -> Academic Performance	- 0.003	0.535	0.593	Not supported

effect = - 0.028,  $t = 1.668$ ,  $p < 0.10$ ) through the use of ChatGPT. Students who were sensitive to rewards were less likely to use ChatGPT and thus experience lower levels of procrastination and memory loss. However, the findings revealed that the indirect effect of sensitivity to rewards on academic performance was insignificant (indirect effect = 0.011,  $t = 1.380$ ,  $p = 0.168$ ). These findings supported hypothesis 10 for procrastination and memory loss only. Finally, the indirect effects of sensitivity to quality on procrastination (indirect effect = 0.010,  $t = 0.582$ , *n.s.*), memory loss (indirect effect = 0.009,  $t = 0.582$ , *n.s.*), and academic performance (indirect effect = - 0.003,  $t = 0.535$ , *n.s.*) through the use of ChatGPT were all insignificant. Therefore, hypothesis 11 was not supported.

## Overall discussion

### Major findings

The recent emergence of generative AI has brought about significant implications for various societal institutions, including higher education institutions. As a result, there has been a notable upswing in discussions among scholars and academicians regarding the transformative potential of generative AI, particularly ChatGPT, in higher education and the risks associated with it (Dalalah & Dalalah, 2023; Meyer et al., 2023; Peters et al., 2023; Yilmaz & Yilmaz, 2023a). Specifically, the dynamics of ChatGPT are still unknown in the context that no study, to date, has yet provided any empirical evidence on why students' use ChatGPT. The literature is also silent on the potential consequences, harmful or beneficial, of ChatGPT usage (Dalalah & Dalalah, 2023; Paul et al., 2023) despite a ban in many institutions across the globe. Responding to these gaps in the literature, the current study proposed workload, time pressure, sensitivity to rewards, and sensitivity



to quality as the potential determinants of the use of ChatGPT. In addition, the study examined the effects of ChatGPT usage on students' procrastination, memory loss, and academic performance.

The findings suggested that those students who experienced high levels of academic workload and time pressure to accomplish their tasks reported higher use of ChatGPT. Regarding the competing hypotheses on the effects of sensitivity to rewards on ChatGPT usage, the findings suggested that the students who were more sensitive to rewards were less likely to use ChatGPT. This indicates that rewards sensitive students might avoid the use ChatGPT for the fear of getting a poor grade if caught. Surprisingly, we found that sensitivity to quality was not significantly related to the use of ChatGPT. It appears that quality consciousness might not determine the use of ChatGPT because some quality conscious students might consider the tasks completed by personal effort as having high quality. In contrast, other quality conscious students might consider ChatGPT written work as having a better quality.

Furthermore, our findings suggested that excessive use of ChatGPT can have harmful effects on students' personal and academic outcomes. Specifically, those students who frequently used ChatGPT were more likely to engage in procrastination than those who rarely used ChatGPT. Similarly, students who frequently used ChatGPT also reported memory loss. In the same vein, students who frequently used ChatGPT for their academic tasks had a poor CGPA. The mediating effects indicated that academic workload and time pressure were likely to promote procrastination and memory impairment among students through the use of ChatGPT. Also, these stressors dampened students' academic performance through the excessive use of ChatGPT. Consistently, the findings suggested that higher reward sensitivity discouraged the students to use ChatGPT for their academic tasks. The less use of ChatGPT, in turn, helped the students experience lower levels of procrastination and memory loss.

### ***Theoretical implications***

The current study responds to the calls for the development of a novel scale to measure the use of ChatGPT and an empirical investigation into the harmful or beneficial effects of ChatGPT in higher education for a better understand of the dynamics of generative AI tools. Study 1 uses a sample of university students to develop and validate the use of ChatGPT scale. We believe that the availability of the new scale to measure the use of ChatGPT may help further advancement in this field. Moreover, study 2 validates the scale using another sample of university students from a variety of disciplines. Study 2 also examines the potential antecedents and consequences of ChatGPT usage. This is the first attempt to empirically examine why students might engage in ChatGPT usage. We provide evidence on the role of academic workload, time pressure, sensitivity to rewards, and sensitivity to quality in encouraging the students to use ChatGPT for academic activities.

The study also contributes to the prior literature by examining the potential deleterious consequences of ChatGPT usage. Specifically, the study provides evidence that the excessive use of ChatGPT can develop procrastination, cause memory loss, and dampen academic performance of the students. The study is a starting point that paws

path for future research on the beneficial or deleterious effects of generative AI usage in academia.

### ***Practical implications***

The study provides important implications for higher education institutions, policy makers, instructors, and students. Our findings suggest that both heavy workload and time pressure are influential factors driving students to use ChatGPT for their academic tasks. Therefore, higher education institutions should emphasize the importance of efficient time management and workload distribution while assigning academic tasks and deadlines. While ChatGPT may aid in managing heavy academic workloads under time constraints, students must be kept aware of the negative consequences of excessive ChatGPT usage. They may be encouraged to use it as a complementary resource for learning instead of a tool for completing academic tasks without investing cognitive efforts. In the same vein, encouraging students to keep a balance between technological assistance and personal effort can foster a holistic approach to learning.

Similarly, policy makers and educators should design curricula and teaching strategies that engage students' natural curiosity and passion for learning. While ChatGPT's ease of use might be alluring, fostering an environment where students derive satisfaction from mastering challenging concepts independently can mitigate overreliance on generative AI tools. Also, recognizing and rewarding students for their genuine intellectual achievements can create a sense of accomplishment that may supersede the allure of quick AI-based solutions. As also noted by Chaudhry et al. (2023), in order to discourage misuse of ChatGPT by the students, the instructors may revisit their performance evaluation methods and design novel assessment criteria that may require the students to use their own creative skills and critical thinking abilities to complete assignments and projects instead of using generative AI tools.

Moreover, given the preliminary evidence that extensive use of ChatGPT has a negative effect on a students' academic performance and memory, educators should encourage students to actively engage in critical thinking and problem-solving by assigning activities, assignments, or projects that cannot be completed by ChatGPT. This can mitigate the adverse effects of ChatGPT on their learning journey and mental capabilities. Furthermore, educators can create awareness among students about the potential pitfalls of excessive ChatGPT usage. Finally, educators and policy makers can develop interventions that target both the underlying causes (e.g., workload, time pressure, sensitivity to rewards) and the consequences (e.g., procrastination, memory loss, and academic performance). These interventions could involve personalized guidance, skill-building workshops, and awareness campaigns to empower students to leverage generative AI tools effectively while preserving their personal learning.

### ***Limitations and future research directions***

Like other study, this study also has some limitations. First, although we used a time-lagged design, as compared to cross-sectional designs used by prior research (e.g., Strzelecki, 2023), we could not completely rule out the possibility of reciprocal relationships. For example, it is also possible that ChatGPT usage may also help lessen the subsequent perceptions of workload. Future research may examine these causal

mechanisms using a longitudinal design. Second, in order to provide a deeper understanding of generative AI usage, future studies may examine how personality factors, such as trust propensity and the Big Five personality traits, relate to ChatGPT usage. Also, an understanding of how these traits shape perceptions of ChatGPT's reliability, trustworthiness, and effectiveness may shed light on the dynamics of user-machine interactions in the context of generative AI.

Moreover, our finding regarding the insignificant effect of quality consciousness on ChatGPT usage warrants further investigation. While some quality conscious students might consider personal effort as a condition to produce quality work, other quality conscious individuals might believe that ChatGPT can help achieve quality in academic tasks. Perhaps, some contextual moderators (e.g., propensity to trust generative AI) may play their role in determining the effects of quality consciousness on ChatGPT usage. In the same vein, fear of punishment may also discourage the use of ChatGPT for plagiarism. As noted by an anonymous reviewer, future studies may probe the benefits associated with the use of generative AI and also compare the dynamics of ChatGPT usage across numerous fields of knowledge (e.g., computer sciences, social sciences) or across gender to examine any differential effects. Finally, future research may probe the effects of ChatGPT usage on students' learning and health outcomes. By investigating how ChatGPT usage impacts cognitive skills, mental health, and learning experiences among students, researchers can contribute to the growing discourse on the role of generative AI in higher education.

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**Author contributions**

MA contributed to the conceptualization of the idea, theoretical framework, methodology, analyses, and the writeup. FAJ and TIK contributed to the data collection, methodology, analyses, and the write-up. All authors read and approved the final manuscript.

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**Availability of data and materials**

The data associated with this research is available upon a reasonable request.

**Declarations****Ethics approval and consent to participate**

The research was explicitly approved by the ethical review committee of the authors' university. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institution.

**Informed consent**

Participants were informed about the study's procedures, risks, benefits, and other aspects before their participation. Only those who gave their consent were allowed to participate in the research.

**Competing interests**

The authors declare that they do not have any competing interests.

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