

AI tutors and emotional support to reduce academic stress among students at Spanish universities

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Abstract. The study aimed to assess how digital tutoring systems with emotional support functions affect students' academic stress in the context of Spanish higher education. The study was conducted using a quasi-experimental design with pre-and post-tests in the control and experimental groups. Initial measurements revealed a prevalence of moderate and high levels of academic stress among the study participants. Following the conclusion of the experiment, a reduction in academic stress, academic anxiety and emotional exhaustion was observed in the experimental group, whilst no significant changes were found in the control group. In the experimental group, the proportion of students with high academic stress decreased from 33.3% to 12.5%, while the mean stress score fell from 3.69 to 2.81 points. A high level of agreement was found between algorithmic recognition of emotional state and students' self-assessments, amounting to 86.3%. The highest ratings were given to the functions explaining the learning material, step-by-step recommendations and brief emotional check-ins. A statistically significant inverse relationship was found between the regularity of artificial intelligence tutor use and the level of academic stress (Pearson's correlation coefficient $r = -0.62$; $p < 0.001$). Regression analysis showed that the greatest contribution to reducing academic stress came from the regularity of digital tutor use, the initial level of academic stress, and trust in the recommendations of artificial intelligence systems. The practical significance of the study lies in substantiating the feasibility of using AI tutors and emotional support systems to support students' independent study, reduce academic stress and improve digital support within the university educational environment

Keywords: personalised learning; mood recognition; learning anxiety; emotional exhaustion; self-regulation; digital tools

INTRODUCTION

Universities were increasingly using artificial intelligence (AI) tutors to personalise learning, provide prompt feedback and support students' independent study. However, academic workload, deadlines, assessment and the need for constant self-organisation remain sources of stress that affect students' motivation to learn, their engagement and their ability to work effectively on educational tasks. There was therefore a need to examine whether AI tutors can fulfil a supportive role in the learning process and contribute to students' emotional self-regulation. Exploring this topic makes it possible to determine the feasibility of integrating mood recognition algorithms and digital emotional support into university learning platforms as a means of reducing academic stress.

In the academic literature, the issue of using artificial intelligence in higher education has been examined from various perspectives. P. González-Rico & M. Lluch

Sintes (2024) had reported that combining personalised mentoring with artificial intelligence tools contributed to the development of self-organisation, communication and responsible decision-making skills. The authors noted that personalised recommendations enabled students to manage their study workload more effectively and adapt more quickly to the demands of the educational environment. A. Hajeer *et al.* (2024) had examined students' perceptions of artificial intelligence tutors in higher education institutions in Spain and Hungary. The data revealed that the majority of participants viewed the possibility of receiving prompt feedback and personalised recommendations positively. Another aspect had been highlighted by H. Galindo-Domínguez *et al.* (2024), who had recorded a high level of readiness among Spanish educators to use artificial intelligence tools. The researchers concluded that the greatest potential of such technologies lay in the personalisation

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of the educational process and the adaptation of learning content to students' individual characteristics. J.-M. Aguado-García *et al.* (2025) had summarised the results of numerous studies on the use of artificial intelligence in higher education. The authors noted that the most consistent positive results were observed in the areas of personalised learning, automated student support and educational data analytics. The study by L.M.G. Gallastegui & R.R. Forradellas (2024) had demonstrated that predictive artificial intelligence models enabled the forecasting of learning difficulties and risks of academic failure. The study's findings had indicated the possibility of early identification of students requiring additional support. The authors had emphasised the importance of integrating predictive mechanisms into digital educational systems.

A systematic review by J.P. López-Goyez *et al.* (2024) had demonstrated a steady increase in the number of studies devoted to intelligent learning systems. A synthesis of the available findings showed that such systems contributed to improved learning outcomes and greater personalisation of the educational process. S.E. Vaca Zambrano *et al.* (2025) had reported a positive impact of personalised learning on students' engagement with the educational process. The findings indicated an improvement in individual learning pathways and an increase in the level of academic engagement. However, the authors did not examine the link between personalisation and students' emotional state. D. Rodríguez Cairo & Y. Ramírez Echavarría (2023) had found that the use of intelligent tutoring systems was accompanied by an improvement in the quality of academic support and the availability of advisory assistance. The researchers noted a reduction in response times to learning enquiries and improved access to educational resources. The main focus, however, was on educational outcomes rather than the psychological consequences of using such technologies. A study by H.H. Ariza (2026b) had demonstrated that the introduction of artificial intelligence tutors contributed to greater personalisation of learning and increased the effectiveness of educational interaction. The author concluded that adaptive recommendations enabled students to plan their own learning activities more effectively. The question of how such solutions had affected levels of academic stress remained outside the scope of the analysis. J.R. Hernández-Herrera *et al.* (2026) had found that AI-based adaptive learning systems allowed for a more flexible approach to addressing students' individual educational needs. The results demonstrated an increase in the level of personalisation and an improvement in indicators of learning interaction. At the same time, the authors did not investigate the potential for using emotional state analysis algorithms in an educational setting.

The analysis carried out showed that previous studies had predominantly focused on the personalisation of learning, adaptive student support mechanisms, the prediction of educational outcomes, and the evaluation of the effectiveness of AI tutors. Issues relating to academic stress, emotional well-being and the functioning of mood recognition algorithms in higher education were considered much less frequently. The interrelationships between the use of AI tutors, digital emotional support and changes in students' academic stress indicators remained understudied. Furthermore, there was limited empirical data on the effectiveness of integrating the educational and support functions of artificial intelligence into the university environment in Spain.

The aim of the study was to determine the impact of AI tutors with emotional state recognition and digital emotional support functions on the level of academic stress among university students in Spain. To achieve this aim, the following research objectives were set: to characterise the sample of study participants and establish the baseline level of academic stress among students; to determine the impact of AI tutors and emotional support systems on indicators of academic stress, academic anxiety and emotional exhaustion; to evaluate the effectiveness of mood recognition algorithms, identify patterns in the use of AI support functions, and determine the factors associated with a reduction in students' academic stress.

MATERIALS AND METHODS

The study used a quasi-experimental design with pre- and post-testing in experimental and control groups from March to May 2026. The eight-week experiment involved 240 full-time undergraduate students aged 18-24 from the Universidad Complutense de Madrid, the Universitat de Barcelona and the Universidad de Valencia. Participants used university learning platforms and provided informed consent. Students receiving psychological treatment or regularly using AI tutors were excluded. Each university recruited 80 students, who were allocated to groups by university, year of study and specialisation. The experimental group used Khanmigo (n.d.), Wysa (n.d.) and Woebot Health (n.d.) at least three times weekly, while the control group used standard digital resources. AI use was measured through platform logs.

Empirical data were collected using two author-designed questionnaires. The first measured academic stress, academic anxiety and emotional exhaustion; the second was completed after the experiment and assessed satisfaction with AI tutors and digital support. Internal consistency was checked using Cronbach's alpha: $\alpha = 0.84$ and $\alpha = 0.87$, respectively. The first questionnaire included socio-demographic items and statements on stress, anxiety, exhaustion and independent study (Table 1).

Table 1. Academic stress questionnaire used in the study

Statement	Measured indicator
I find it difficult to start working on academic tasks without external assistance.	Learning autonomy
A large number of deadlines creates a constant feeling of pressure.	Academic stress

Table 1. Continued

Statement	Measured indicator
I experience strong anxiety before examinations or tests.	Academic anxiety
I find it difficult to maintain concentration while completing academic tasks.	Concentration
I tend to postpone major assignments until the last days before the deadline.	Procrastination
My academic workload causes emotional fatigue.	Emotional exhaustion
After several hours of studying, find it difficult to remain productive.	Cognitive fatigue
I confidently plan and organise my study time.	Self-organisation
I quickly recover my ability to concentrate after intensive studying.	Self-regulation
The learning process was often accompanied by a feeling of psychological exhaustion.	Psychological exhaustion

Source: compiled by the author

All statements were assessed on a five-point Likert scale, from 1, “strongly disagree”, to 5, “strongly agree”. Higher scores indicated greater expression of the measured indicator. The survey was completed remotely through digital forms on university learning platforms after informed consent had been provided. The

baseline questionnaire was administered before the intervention and took about 12 minutes. After eight weeks, all students completed the same questionnaire again. The experimental group also assessed the usefulness of Khanmigo (n.d.), Wysa (n.d.) and Woebot Health (n.d.) functions (Table 2).

Table 2. AI support satisfaction questionnaire used in the study

Statement	Measured indicator
Khanmigo explanations helped understand learning material more quickly.	Perceived usefulness of academic explanations
Step-by-step recommendations made it easier to complete complex tasks.	Task-structuring support
Wysa emotional check-ins helped assess my current emotional state.	Emotional self-assessment
Wysa recommendations helped restore concentration during studying.	Concentration recovery
Dialogues with Woebot Health helped better understand the causes of academic tension.	Emotional reflection
Using digital tutors reduced the time needed to find relevant information.	Time efficiency
I trusted the recommendations generated by artificial intelligence systems.	Trust in AI recommendations
The use of AI made the organisation of learning more convenient.	Learning organisation
I am willing to use such systems in my further studies.	Intention to continue use
Overall, it was satisfied with the use of AI support.	Overall satisfaction

Source: compiled by the author

Statistical analysis included absolute and relative frequencies, means, standard deviations and 95% confidence intervals. Pre- and post-test indicators were compared using the paired t-test or, where normality was not confirmed, the Wilcoxon test. Between-group differences were assessed using the Mann-Whitney U-test and Fisher’s exact test. Pearson’s coefficient was used for correlation analysis, and multiple regression with Wald’s test was applied to examine selected predictors. Statistical significance was set at $p < 0.05$. Agreement between AI-based emotion recognition and students’ self-assessments was calculated in the experimental group. Four categories were used: calm, stressed, anxious and emotionally exhausted. Matching AI and student classifications were expressed as a percentage of all completed check-ins. Participants also rated academic explanations, step-by-step recommendations, emotional check-ins, reflective dialogues and motivational messages on a five-point usefulness scale. The study followed the Code of Ethics of the American Sociological Association (2025), the ICC/ESOMAR International Code of Conduct for Market, Public and Social Research and Data Analysis (2025) and the Guidelines on Ethics and Data Protection (European Commission, 2021). Participation was voluntary and required electronic informed consent.

Students received information on the study purpose, duration, collected data and withdrawal rights. Personal data were anonymised before analysis, and results were reported in aggregated form. The study was limited to three Spanish universities, an eight-week intervention and self-report measures, which were considered when interpreting the results. The study was limited by the inclusion of students from three Spanish universities, the eight-week intervention period and the use of self-report questionnaires.

RESULTS AND DISCUSSION

Baseline characteristics of the sample and indicators of academic stress among students

The initial stage of the study focused on the composition of the sample and the baseline measurement of academic stress, academic anxiety and emotional exhaustion before the introduction of AI-based support tools. The study included 240 students enrolled at three Spanish universities. For further analysis, the overall sample was distributed according to year of study, academic specialisation and study group. Students from the three universities were allocated equally between the experimental and control groups: each institution contributed 40 students to the experimental group and 40 students to the control group (Table 3).

Table 3. Distribution of study participants by year of study, academic specialisation and study group

Variable	Category	N	%
Year of study	First year	58	24.2
	Second year	61	25.4
	Third year	63	26.3
	Fourth year	58	24.2
Academic specialisation	Education	72	30.0
	Psychology	56	23.3
	Humanities	58	24.2
	Social Sciences	54	22.5
Study group	Experimental group	120	50.0
	Control group	120	50.0
Total sample	All participants	240	100.0

Source: compiled by the author

The distribution of participants showed that all years of study and academic specialisations were represented in the sample. First-year students accounted for 58 participants (24.2%), second-year students for 61 (25.4%), third-year students for 63 (26.3%) and fourth-year students for 58 (24.2%). By academic specialisation, the largest group consisted of students enrolled in Education programmes, with 72 participants (30.0%). Psychology programmes were represented by 56 students (23.3%), Humanities by 58

students (24.2%) and Social Sciences by 54 students (22.5%). The experimental and control groups each comprised 120 participants. The mean age of the students was 20.8 years ($SD = 1.7$). Before the intervention, the baseline indicators of the experimental and control groups were compared. This comparison was conducted to determine whether the groups had similar initial levels of academic stress, academic anxiety and emotional exhaustion before the use of AI-based academic and emotional support tools (Table 4).

Table 4. Baseline indicators of academic stress, academic anxiety and emotional exhaustion in the experimental and control groups

Indicator	Experimental group M (SD)	Control group M (SD)	p-value
Academic stress	3.69 (0.60)	3.65 (0.62)	>0.05
Academic anxiety	3.60 (0.57)	3.56 (0.58)	>0.05
Emotional exhaustion	3.22 (0.55)	3.20 (0.56)	>0.05

Note: values were presented as mean scores and standard deviations on a five-point Likert scale. Differences between the experimental and control groups were not statistically significant at $\alpha = 0.05$

Source: compiled by the author

The baseline values showed no statistically significant differences between the experimental and control groups. This indicated that both groups had comparable initial indicators of academic stress, academic anxiety and emotional exhaustion before the intervention. Therefore, subsequent changes could be analysed without attributing them to unequal starting conditions. Following the baseline comparison of the experimental and control groups, the overall distribution of participants according to levels of academic stress was examined. The analysis showed that academic stress was widespread among the students included in the study. More than half of the participants demonstrated a moderate level of academic stress (51.7%, $n = 124$), while nearly one-third exhibited a high level of academic stress (32.5%, $n = 78$). In contrast, only 15.8%

of students ($n = 38$) were classified as having a low level of academic stress. The predominance of moderate and high stress levels indicated that academic stress represented a common feature of the students' educational experience at the beginning of the study. These findings characterised the baseline condition of the sample prior to the implementation of AI-based academic and emotional support tools and provided a reference point for evaluating subsequent changes during the intervention. The next stage of the baseline analysis concerned the academic activities most often associated with stress. The assessment included deadlines and accumulation of assignments, examination preparation, difficulties in self-organisation, interaction with instructors and work in academic groups (Table 5).

Table 5. Structure of academic stress factors at the initial stage

Academic stress factor	Mean score (M)	SD
Deadlines and accumulation of assignments	4.12	0.58
Examination preparation	3.94	0.63
Difficulties in self-organisation	3.51	0.67

Table 5. Continued

Academic stress factor	Mean score (M)	SD
Interaction with instructors	2.83	0.71
Work in academic groups	2.67	0.74

Note: scores were presented as mean values on a five-point Likert scale, where 1 indicates the lowest manifestation of the factor and 5 indicates the highest. SD = standard deviation

Source: compiled by the author

The highest mean scores were recorded for deadlines and accumulation of assignments ($M = 4.12$; $SD = 0.58$), examination preparation ($M = 3.94$; $SD = 0.63$) and difficulties in self-organisation ($M = 3.51$; $SD = 0.67$). Lower scores were recorded for interaction with instructors ($M = 2.83$; $SD = 0.71$) and work in academic groups ($M = 2.67$; $SD = 0.74$). These results showed that academic stress at the initial stage was mainly associated with the organisation of individual learning activity, preparation for assessment and the distribution of workload before deadlines. After the baseline stage, students in the experimental group were provided with access to AI-based academic and emotional support tools. Khanmigo was used to explain learning material, clarify complex topics, ask guiding questions and support students in solving academic tasks independently. Wysa and Woebot Health were used for emotional check-ins, short self-regulation exercises and reflective dialogues related to anxiety, fatigue and loss of concentration. The control group continued studying without these digital support tools. This organisation of the intervention made it possible to compare subsequent changes in academic stress, academic anxiety and emotional exhaustion between students who used AI-based support and students who followed the usual learning process. Before comparing the indicators of the experimental and control groups, it was useful to compare the proportion of students with different levels of academic stress. This presentation made it possible to assess the homogeneity of the groups in terms of the distribution of participants with low, medium and high levels of academic stress even before the use of AI tutors and emotional support systems began (Fig. 1).

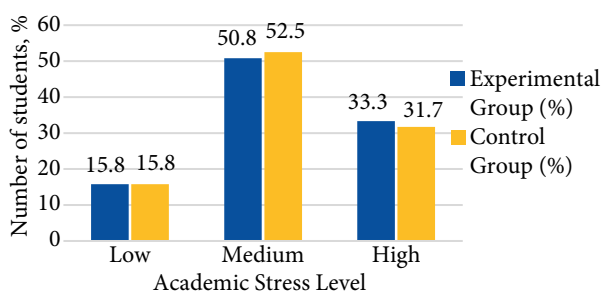


Figure 1. Comparison of initial levels of academic stress in the experimental and control groups

Note: the data were presented as a percentage of the total number of participants in each group ($n = 120$). The proportion of students with low, medium and high levels of academic stress was calculated separately for the experimental and control groups prior to the introduction of AI tutors. No statistically significant differences were found between the groups ($p > 0.05$)

Source: compiled by the author

The distribution of participants by year of study, degree programme and university showed no statistically significant differences between the experimental and control groups. The results of Fisher's exact test for the main categorical indicators did not reach the established significance level. This confirmed that the groups were comparable at the start of the experiment. Initial measurements also showed that academic stress was common among a significant proportion of students. Moderate and high levels of academic stress predominated in the sample, while low stress was recorded in a smaller proportion of participants. Baseline indicators of academic anxiety and emotional exhaustion also remained at a level that allowed further assessment of changes during the intervention. Thus, the results of the initial stage confirmed the balance of the sample and the absence of statistically significant differences between the experimental and control groups before the use of AI-based academic and emotional support tools.

The impact of AI tutors and emotional support systems on students' academic stress

Following the eight-week period of using AI tutors, changes were observed not only in the quantitative indicators of academic stress but also in the nature of the students' study habits. Participants in the experimental group more frequently reported a more organised allocation of study time, fewer instances of leaving tasks until the last few days, and a reduced need to seek additional explanations independently after working through the study material. The results indicated that the use of Khanmigo (n.d.), Wysa (n.d.) and Woebot Health (n.d.) influenced not only the subjective perception of the academic workload but also specific components of learning behaviour that had previously been associated with the onset of academic stress. Eight weeks after the start of using the digital tools, the average level of academic stress in the experimental group fell from 3.69 to 2.81 points ($SD = 0.56$; $p < 0.001$). The changes were fairly uniform across students from different universities and year groups, indicating that the observed effect was not dependent on the specific educational environment. Above all, the aspects of academic activity that had created the greatest burden at the initial stage were the ones that changed. Students reported fewer instances were having to complete several written assignments simultaneously led to a loss of control over the learning process. Some participants noted that, after using Khanmigo, complex topics became easier to work through without having to refer to external information

resources. The explanation of the learning material in a dialogue format allowed misunderstandings of individual concepts to be cleared up more quickly, so re-reading the same sections became less common. There were also noticeable changes in how study time was planned. Whilst at the start of the study a significant proportion of students completed tasks without a clear time allocation, after the experiment concluded, participants more frequently reported using short study sessions, regularly checking their progress, and tackling large projects in stages. This helped to reduce the workload in the run-up to deadlines (Fig. 2).

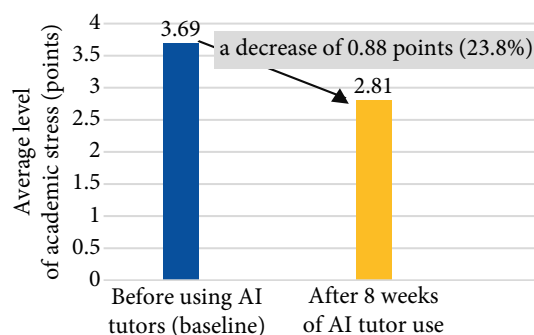


Figure 2. Change in the average level of academic stress in the experimental group before and after using AI tutors

Note: the diagram shows the mean academic stress scores of students in the experimental group before the start of AI tutor use ($M = 3.69$; $SD = 0.60$) and after eight weeks of use ($M = 2.81$; $SD = 0.56$). The reduction in the mean score was 0.88 points (23.8%). A statistically significant difference between the measurements was confirmed by Student's t-test for paired samples ($p < 0.001$)

Source: compiled by the author

Individual responses from students showed that Khanmigo was used primarily as a support tool whilst carrying out specific learning activities. Students entered a section of a problem, asked for an explanation of the sequence of steps to solve it, clarified the meanings of individual concepts from the lecture material, and checked whether had constructed their own line of reasoning correctly. In some cases, the tutor was used to break down a large task into shorter stages: identifying the first step, drawing up a plan for the answer, checking an interim result and formulating a final conclusion. Such actions reduced the number of repeated attempts at the same task, as students received explanations the moment, encountered difficulties. Most often, this related to preparation for tests, written assignments and group projects, where it was necessary to quickly understand the requirements, clarify the logic of the answer or check the sequence of reasoning. The results showed that it was not the automation of learning itself that contributed to a reduction in academic stress, but rather the availability of personalised explanations and the opportunity to receive feedback whilst carrying out learning tasks. The interpretation of these results was

further supported by A. Mehrad *et al.* (2025), who had examined educational stress and the use of artificial intelligence tools among international students in Spanish higher education. Their findings had shown that AI tools could function not only as academic resources, but also as means of reducing uncertainty, language-related difficulties and adaptation problems within an unfamiliar institutional environment. This position was relevant to the study, since the decrease in academic stress was connected not only with lower workload pressure, but also with students' greater ability to organise everyday learning practices. This interpretation was also consistent with the approach proposed by R. Sajja *et al.* (2024), who had developed an artificial intelligence-enabled assistant for personalised and adaptive learning in higher education. Their model had combined accessible explanations, knowledge assessment, personalised learning pathways, quizzes and flashcards as means of reducing cognitive load. A similar mechanism was observed in the study: Khanmigo helped students clarify complex concepts, check the logic of their reasoning and divide larger tasks into shorter stages. Therefore, the reduction in academic stress was associated not with the automation of learning, but with the availability of adaptive support at the moment when students encountered difficulty. Comparable conclusions had been reached by F.A. Flores Limo *et al.* (2023), who had examined ChatGPT as a virtual tutor for personalised learning experiences, and by G. Sornavalli *et al.* (2025), who had considered artificial intelligence as a tool for adapting learning support to students' pace, difficulties and individual educational needs. In the study, this function was reflected in students' use of Khanmigo for explanations, task sequencing and feedback during independent work. These forms of support helped maintain control over the learning process, especially when several assignments or assessments had to be managed simultaneously. The behavioural dimension of these changes corresponded to the case study by A. Baillifard *et al.* (2025), in which effective learning with a personal AI tutor had been analysed through the interaction between individualised assistance and students' learning strategies. The authors had shown that personal AI tutoring was linked to timely explanations, active work with tasks and support during the learning process. In the study, this relationship was reflected in the transition from irregular task completion to shorter study sessions, interim progress checks and staged work on larger assignments. Thus, the decrease in academic stress was connected with changes in learning behaviour rather than with the isolated use of digital explanations. Before comparing the results, the average academic stress scores in the experimental and control groups were compared following the conclusion of the experiment. This made it possible to assess whether the use of AI tutors was accompanied by statistically significant changes compared with students who studied without digital emotional support (Table 6).

Table 6. Comparison of academic stress indicators in the experimental and control groups after the experiment had concluded

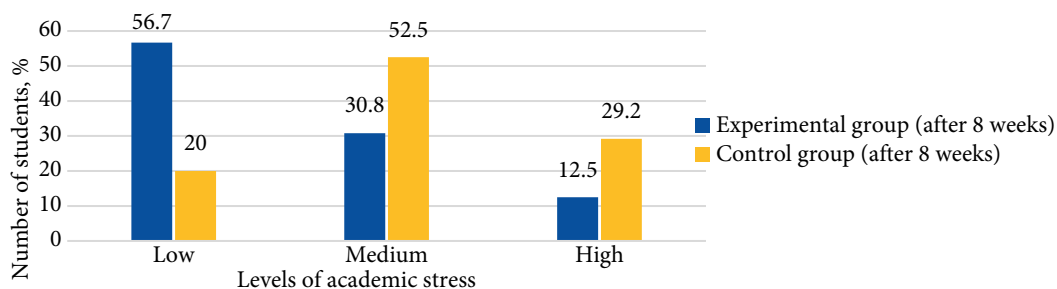
Indicator	Experimental group (N = 120)	Control group (N = 120)	Statistical test	p-value
Mean academic stress score, M (SD)	2.81 (0.56)	3.57 (0.60)	U = 4638	≤0.001
Students with low stress, n (%)	68 (56.7)	24 (20.0)	Fisher's exact test	≤0.001
Students with moderate stress, n (%)	37 (30.8)	61 (50.8)	Fisher's exact test	≤0.001
Students with high stress, n (%)	15 (12.5)	35 (29.2)	Fisher's exact test	0.002

Note: M = mean; SD = standard deviation. Academic stress was assessed using a five-point Likert scale. Differences between groups were evaluated using the Mann-Whitney U test for continuous variables and Fisher's exact test for categorical variables. Statistical significance was established at $\alpha = 0.05$

Source: compiled by the author

The results showed that, after eight weeks of using AI tutors, the experimental group was characterised by a lower average level of academic stress and a higher proportion of students with low levels of academic stress compared to the control group. At the same time, the number of participants with high levels of academic stress in the experimental group decreased significantly. The observed differences between the experimental and control groups were consistent with the conclusions of X. Zhang *et al.* (2025), who had examined the effectiveness of AI-powered tutoring systems in improving learning outcomes. The study had shown that personalised instruction, timely feedback and adaptation to students' needs could support academic progress. In the research, these mechanisms were reflected not only in the organisation of learning activities, but also in lower stress indicators among students who regularly used AI tutors. This suggested that the effect of AI tutoring was not limited to academic performance, since it also helped stabilise study behaviour, reduce uncertainty and ease deadline-related

pressure. The experimental nature of these results may also be considered in relation to G. Kestin *et al.* (2025), who had evaluated AI tutoring through a randomised controlled trial in an authentic educational setting. Their study had shown that a research-based AI tutoring design could produce stronger learning outcomes than in-class active learning. Although the study focused on academic stress rather than achievement, both studies demonstrated the value of AI support under conditions close to ordinary higher education practice. In this research, the advantage of the experimental group was expressed through lower stress scores, a higher proportion of students with low stress and fewer reports of deadline-related overload. Upon completion of the experiment, it was appropriate to compare the distribution of students by levels of academic stress in the experimental and control groups. This comparison made it possible to assess how the proportion of participants with low, medium and high levels of academic stress had changed after eight weeks of using AI tutors and emotional support systems (Fig. 3).

**Figure 3.** Comparison of academic stress levels in the experimental and control groups after the experiment concluded

Note: the diagram shows the distribution of students in the experimental (n = 120) and control (n = 120) groups by levels of academic stress following the completion of the eight-week experiment. Levels of academic stress were determined according to three categories based on the total score on the Likert scale: low (1.00-2.33 points), medium (2.34-3.66 points) and high (3.67-5.00 points). Differences between the groups were statistically significant according to Fisher's test ($p < 0.05$)

Source: compiled by the author

Differences were also evident in the way learning tasks were carried out. Students in the control group reported significantly more often that had a backlog of unfinished work, that had to work in the evenings before deadlines, and that had difficulty concentrating whilst preparing for tests. Participants in the experimental group, by contrast, more often noted that completed tasks gradually, used Khanmigo's recommendations to structure the learning

material, and were less likely to revisit exercises had already completed due to doubts about the correctness of their answers. These changes indicated that the use of the AI tutor primarily influenced the organisation of learning activities, whilst the reduction in academic stress was a consequence of more effective management of the learning process. Before comparing individual psychological indicators, account was taken not only of changes in academic

stress but also of the states that accompanied the study load throughout the experiment. Academic anxiety, emotional exhaustion and satisfaction with the learning process made

it possible to determine whether the use of AI support had an impact on the students' broader experience whilst completing academic tasks (Table 7).

Table 7. Changes in academic anxiety, emotional exhaustion and satisfaction with the learning process

Indicator	Before AI support M (SD)	After AI support M (SD)	Change	p-value
Academic anxiety	3.60 (0.57)	2.74 (0.53)	-0.86	<0.001
Emotional exhaustion	3.22 (0.55)	2.51 (0.50)	-0.71	<0.001

Note: the values were presented as mean scores and standard deviations on a five-point Likert scale. A negative change indicates a decrease in the indicator following the use of AI support. The statistical significance of the differences between the two measurements was tested using Student's t-test for paired samples; the significance level was set at $\alpha = 0.05$

Source: compiled by the author

After the completion of the experiment, students in the experimental group additionally completed the AI Support Satisfaction Questionnaire. The mean satisfaction score was 4.09 (SD = 0.58), indicating a positive evaluation of the accessibility of explanations, the pace of learning, emotional check-ins and self-regulation tools. After eight weeks of using AI support, the reduction in academic anxiety was accompanied by a lower frequency of reports of uncertainty before tests, rechecking of tasks already completed, and difficulties in starting independent work. A similar mechanism was described in a study by Q. Zafar *et al.* (2026), where the use of AI tools was examined in terms of its impact on students' emotional regulation and learning anxiety. The authors found that more active use of AI support was associated with higher levels of emotional regulation and lower levels of learning anxiety. A key point for comparison with the findings was that the reduction in anxiety was attributed not only to access to learning information, but also to the opportunity to receive support whilst performing complex academic tasks. In this study, this relationship manifested itself through reduced uncertainty prior to tests, a reduced need to repeatedly check tasks already completed, and more frequent use of brief self-regulatory actions. At the same time, this study specified the impact of AI support through the combination of Khanmigo's educational tutoring with Wysa's emotional check-ins and Woebot Health's reflective dialogues.

Reduced emotional exhaustion indicated a better distribution of workload throughout the week, whilst increased satisfaction with the learning process reflected a more positive perception of the accessibility of explanations, the pace of learning and digital support. Students' responses indicated that reduced anxiety was accompanied by a change in daily study habits. Participants reported less frequently needing to check completed tasks multiple times, felt less anxious before tests, and were less likely to delay starting work due to uncertainty about their own knowledge. A distinct effect was linked to the use of Wysa and Woebot Health as tools for short-term emotional self-regulation. A similar correlation between emotional support and learning activities was also observed in the study by Y. Zong & L. Yang (2025). The authors considered artificial intelligence as a component of social-emotional learning and demonstrated that taking students' emotional

reactions into account whilst interacted with digital systems was accompanied by an increase in their engagement with the learning process and an improvement in their emotional well-being. The results obtained in this study complemented the findings cited above. A reduction in academic stress was associated with the regular use of brief emotional check-ins and reflective dialogues, which helped students to identify signs of burnout in a timely manner, adjust their study routine and regain concentration more quickly. Unlike the study by Y. Zong & L. Yang, the main focus was not on changes in academic engagement, but on the dynamics of academic stress, academic anxiety and emotional exhaustion.

Throughout the academic day, students carried out emotional check-ins: indicated their current state, selected options such as tension, fatigue, anxiety or loss of concentration, and then received brief recommendations. Most often, these recommendations involved taking a 5-10-minute break, doing a breathing exercise, breaking the task down into smaller parts, returning to a specific step, or noting the cause of the tension in a short text message. In their responses, students described these interactions as a way to halt the build-up of fatigue more quickly whilst working independently. Some participants noted that after checking in, did not stop studying altogether, but changed their approach: took a short break, returned to a simpler part of the task, clarified the next step in Khanmigo, or postponed part of the work to another time slot. This reduced the number of instances where fatigue led to the task being put aside entirely. The satisfaction score for the learning process also changed. Whilst the average score at the start of the study was 3.18, it rose to 4.09 by the end of the experiment. Most often, students attributed the positive changes to the speed at which explanations were provided, the ability to work at their own pace, concise self-regulation tools, and the fact that did not need to wait for a lecturer's consultation to resolve specific learning difficulties. This position was consistent with the findings of A. Gurung *et al.* (2025), who had shown that human tutoring could strengthen the learning effect of AI tutor use. Their study had demonstrated that the impact of AI-supported learning depended not only on the technological quality of the tutor but also on the presence of pedagogical guidance that helped students interpret feedback and

apply it productively. In the study, this idea was reflected in students' perception of AI tools as supplementary instruments for independent work between classroom sessions. Therefore, the reduction in academic stress should be interpreted as the result of combined digital and pedagogical support, rather than as an argument for replacing lecturer involvement. At the same time, the majority of participants did not view AI as a complete replacement for a lecturer. The prevailing view in the responses was that digital systems were most useful during independent study between classroom sessions and when completing homework assignments. This stance taken by the students highlighted the issue of the balanced use of AI in higher education, as discussed by B. Klimova & M. Pikhart (2025). Author's review demonstrated that artificial intelligence can support personalised learning, psychological support and the effectiveness of educational communication; however, its

excessive use was associated with risks of digital fatigue, technostress, social isolation and a reduction in face-to-face interaction between participants in the educational process. In this study, such risks were partially mitigated by the very design of the experiment: Khanmigo, Wysa and Woebot Health were used as supplementary tools between classroom sessions, rather than as a substitute for teaching support. The results showed that the positive effect of AI support was linked to its measured use for independent work, emotional check-ins and brief reflective activities, rather than to the transfer of all educational interaction to a digital environment. To verify the validity of the identified changes, a comprehensive statistical analysis was carried out, which made it possible to assess both the differences between repeated measurements and the results of the comparison between the experimental and control groups after the use of AI tutors had ended (Table 8).

Table 8. Results of the statistical analysis of the effectiveness of AI tutors

Indicator	Statistical test	Test value	P-value	Effect size	Interpretation
Academic stress	Paired samples t-test	t = 12.84	<0.001	Cohen's d = 0.91	Large effect
Academic anxiety	Paired samples t-test	t = 11.63	<0.001	Cohen's d = 0.84	Large effect
Emotional exhaustion	Paired samples t-test	t = 9.94	<0.001	Cohen's d = 0.73	Medium to large effect
Academic stress distribution	Fisher's exact test	χ^2 equivalent = 14.27	<0.001	Cramer's V = 0.31	Moderate association
Post-intervention group comparison	Mann-Whitney U test	U = 4638	<0.001	r = 0.42	Moderate effect
Non-normal indicators	Wilcoxon signed-rank test	Z = -7.86	<0.001	r = 0.51	Large effect

Note: the paired t-test was used to compare the experimental group's indicators before and after the use of AI tutors. The Wilcoxon test was used for indicators whose distribution did not follow a normal distribution. The Mann-Whitney U test was used to compare the experimental and control groups after the experiment had concluded, whilst Fisher's exact test was used to compare the proportions of students with different levels of academic stress. The level of statistical significance was set at $\alpha = 0.05$

Source: compiled by the author

In addition to the comparison of pre- and post-experiment indicators, Pearson's correlation analysis was conducted to determine the relationships between the intensity

of AI tutor use, emotional check-ins, satisfaction with AI support and changes in academic stress, academic anxiety and emotional exhaustion (Table 9).

Table 9. Correlations between AI support use and changes in students' psychological indicators

Variable pair	Pearson's r	P-value	Interpretation
Frequency of AI tutor use and reduction in academic stress	-0.58	<0.001	Moderate negative correlation
Frequency of AI tutor use and reduction in academic anxiety	-0.51	<0.001	Moderate negative correlation
Frequency of emotional check-ins and reduction in emotional exhaustion	-0.47	<0.001	Moderate negative correlation
Satisfaction with AI support and reduction in academic stress	-0.54	<0.001	Moderate negative correlation
Trust in AI recommendations and reduction in academic stress	-0.49	<0.001	Moderate negative correlation
Agreement between algorithmic emotion recognition and self-assessment	0.63	<0.001	Strong positive correlation

Note: Pearson's correlation coefficient was used to assess the relationship between AI support variables and changes in students' psychological indicators. Negative coefficients indicate that more frequent or more positively evaluated use of AI support was associated with lower levels of academic stress, academic anxiety and emotional exhaustion after the experiment. Statistical significance was established at $\alpha = 0.05$

Source: compiled by the author

The correlation analysis showed that more frequent use of AI tutors was associated with lower post-experiment levels of academic stress and academic anxiety. Emotional check-ins were also related to reduced emotional exhaustion. A positive correlation between algorithmic emotion recognition and students' self-assessments confirmed that the digital systems reflected the

students' reported emotional states with sufficient consistency. Alongside testing for statistical significance, identified which characteristics of the learning process were most strongly associated with a reduction in academic stress. To this end, the results were summarised using a regression model, which enabled to assess the contribution of each predictor (Fig. 4).

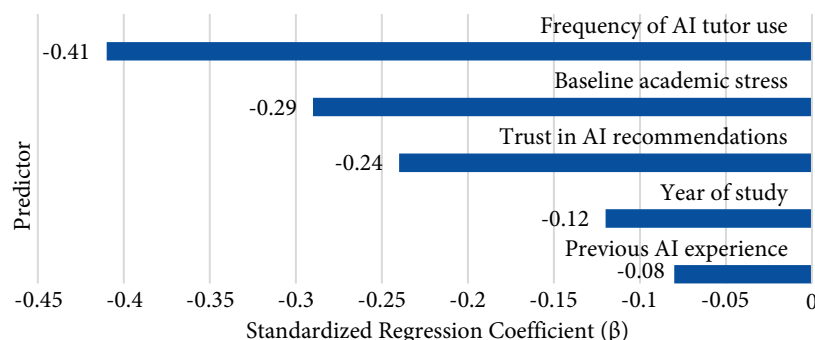


Figure 4. Contribution of individual factors to the reduction in academic stress based on the results of regression analysis

Note: the diagram shows the standardised regression coefficients (β) obtained from the results of multiple regression analysis. Higher absolute values of β indicate a stronger contribution of the corresponding predictor to the reduction in academic stress

Source: compiled by the author

Calculation of the effect size showed that the changes in academic stress corresponded to a large effect (Cohen's $d = 0.91$), whilst values of 0.84 and 0.73 were obtained for academic anxiety and emotional exhaustion, respectively. This indicated that the observed changes were not only statistically significant but also had practical implications for the organisation of university support for students. The results showed that combining Khanmigo's academic support with the emotional support systems Wysa and Woebot Health helped to reduce academic stress, improve self-regulation of learning activities and increase satisfaction with the educational process. The most significant changes were observed in the organisation of independent study, the planning of study time and the reduction of stress associated with challenging academic tasks, indicating that the use of AI-based support tools was accompanied by improvements in several aspects of students' academic self-management.

The effectiveness of mood recognition algorithms and AI-supported student support functions

Once changes in academic stress levels had been established, it became necessary to assess how effectively the emotion recognition algorithms reflected students' actual experiences and how individual AI support functions were linked to changes in psychological indicators. The results obtained made it possible to compare the algorithmic determination of emotions with the participants' self-assessments, to trace the relationship between the intensity of digital tutor use and the dynamics of academic stress, and to identify the features that students considered most useful when completing academic tasks. A comparison of the

results of automatic emotional state recognition with students' self-assessments revealed a fairly high level of agreement between them. A similar approach was presented in the work of S. Javed *et al.* (2025), where the recognition of students' emotional signals was considered a prerequisite for personalised support in a virtual learning environment. The authors demonstrated that more accurate identification of emotional reactions was associated with enhanced social-emotional learning and individualised academic support. In their study, emotional signals were treated not as a secondary parameter of digital interaction, but as information enabling timely adjustments to the nature of learning support. This was consistent with the findings presented here, where algorithmic identification of states of calm, tension, fatigue and anxiety was used to select brief recommendations in Wysa and Woebot Health. The difference lay in the fact that, in this study, the accuracy of emotion recognition was verified by comparing it with students' self-assessments, whilst the subsequent interpretation was linked to changes in academic stress.

In most cases, the Wysa and Woebot Health algorithms correctly identified the general nature of the emotional state that students reported during brief check-ins. The highest agreement was observed for assessments of tension, fatigue, motivation and calmness. Lower agreement was observed for feelings of uncertainty and anxiety, as some students described these as interrelated experiences. Before presenting the summarised results, individual emotional states recorded during check-ins in Wysa and Woebot Health were compared. This made it possible to determine for which states algorithmic recognition most accurately corresponded to the students' self-assessments (Table 10).

Table 10. Agreement between algorithmic recognition of emotional states and students' self-assessments

Emotional state	Agreement with student self-assessment (%)	Interpretation
Calmness	92.5	Very high agreement
Tension	89.2	High agreement
Fatigue	87.4	High agreement
Motivation	84.8	High agreement
Anxiety	82.1	Moderate to high agreement

Table 10. Continued

Emotional state	Agreement with student self-assessment (%)	Interpretation
Uncertainty	79.7	Moderate agreement
Mean agreement	86.3	High overall agreement

Note: the percentage of agreement reflects the proportion of cases in which the algorithmic determination of emotional state coincided with the student's self-assessment during a brief emotional check-in. The data were aggregated from the results of students' interactions with Wysa and Woebot Health over the eight-week duration of the experiment

Source: compiled by the author

Individual student responses corroborated the quantitative results. Before starting challenging written assignments, participants often described their state as "tension" or "uncertainty". After completing the brief check-in, the system recommended taking a short break, outlining the first stage of the task, or starting with the simplest part. Following this, the majority of students reassessed their state as less tense, which corresponded to the changes simultaneously recorded by the algorithm. A noticeable difference remained between short-term academic anxiety and persistent emotional exhaustion. Whilst the system identified brief emotional reactions with reasonable accuracy, signs of accumulated fatigue more often required several consecutive check-ins. In such cases, the algorithm took into account the repetition of responses and gradually adjusted the content of its recommendations, suggesting not only breathing exercises but also adjustments to the study routine, planning of breaks or a review of the sequence of tasks. The results showed that the algorithms used were suitable for providing pedagogical support to students, as enabled changes in emotional state to be identified in a timely manner without the need for constant intervention by a teacher or psychologist. Verifying the accuracy of recognition provided a basis for assessing whether the intensity of use of digital tutors was linked to changes in academic stress.

The results showed that the intensity of use of AI tutors was directly linked to a reduction in academic stress. Students who worked regularly with Khanmigo, Wysa and Woebot Health throughout the experiment demonstrated a more pronounced improvement compared with participants who used digital support only occasionally. For further analysis, the experimental group was provisionally divided into three categories based on the average number of interactions with the systems per week. The first category comprised students who used the AI no more than twice a week; the second, between three and five times; and the third, more than five interactions per week. The greatest reduction in academic stress was recorded among students in the third category. On average, their score fell by 1.07 points. In the second category, the reduction was 0.83 points, whilst among participants with the lowest frequency of use of digital tutors, the change did not

exceed 0.39 points. A similar pattern was observed with regard to academic anxiety. Regular use of the system was accompanied by fewer reports of difficulties in starting tasks, fear of making mistakes, and double-checking answers that had already been prepared. Students more often reported that began work immediately after receiving an assignment, rather than putting it off until the last few days. The nature of interaction with the various digital tools also differed. Khanmigo was most frequently used to explain specific concepts, check the logic behind problem-solving, and structure written assignments. Wysa was used mainly after several hours of continuous study or before beginning exam preparation, when students reported feeling tired or having difficulty concentrating. Woebot Health was used for short reflective dialogues that helped students assess their own emotional state and identify the causes of stress. The frequency of use varied depending on the stage of the semester.

This dynamic corresponded to the position developed by H.E. Sari *et al.* (2024), who had examined the improvement of educational outcomes through adaptive learning systems using artificial intelligence. In their study, adaptive learning had been associated with the ability of digital systems to modify content, feedback and learning pathways according to students' progress and current educational needs. This perspective was relevant to the findings because the frequency and purpose of using Khanmigo, Wysa and Woebot Health changed as the semester progressed. During the final weeks, AI support was used more intensively for explanations, answer checking and emotional check-ins, which indicated that adaptive digital support became more significant when academic pressure increased. The increase in the number of enquiries to AI tools reflected changes in students' learning needs over the course of the semester. In the early weeks, digital tutors were used primarily to help students adapt to the format of the course and to clarify specific aspects of the material. As the final assessment approached, interactions became more regular: Khanmigo was used more frequently to explain the material and check the logic of answers, whilst Wysa and Woebot were used for brief emotional check-ins following longer study sessions (Table 11).

Table 11. Frequency of use of AI tutors depending on the stage of the academic semester

Stage of the semester	Khanmigo interactions m (sd)	Wysa check-ins m (sd)	Woebot Health sessions m (sd)	Total AI interactions m (sd)
Weeks 1-2	2.4 (0.8)	1.6 (0.7)	1.2 (0.6)	5.2 (1.4)
Weeks 3-4	3.1 (0.9)	2.0 (0.8)	1.5 (0.7)	6.6 (1.6)

Table 11. Continued

Stage of the semester	Khanmigo interactions m (sd)	Wysa check-ins m (sd)	Woebot Health sessions m (sd)	Total AI interactions m (sd)
Weeks 5-6	3.8 (1.0)	2.4 (0.9)	1.8 (0.8)	8.0 (1.8)
Weeks 7-8	4.6 (1.1)	3.0 (1.0)	2.1 (0.8)	9.7 (2.0)

Note: values were presented as the average number of interactions per student with the respective AI tool over the course of a week. M = mean; SD = standard deviation. The increase in the frequency of interactions during weeks 7-8 coincided with the period of preparation for the final assessment

Source: compiled by the author

The students' responses regarding the nature of their use of the systems were also revealing. A significant proportion of participants reported that had gradually stopped turning to AI only when difficulties arose. Instead, digital tutors began to be used as a tool for advance planning of their studies: to draw up a brief study plan, check progress, or assess their readiness for a test. This change in behaviour was accompanied by a more even distribution of the study load throughout the week and fewer instances of several major tasks being completed simultaneously in the run-up to deadlines. The findings can be interpreted in relation to M.P. Pratama *et al.* (2023), who had considered artificial intelligence as a means of organising personalised learning through the adaptation of educational content to students' individual needs. Their study had shown that AI-based learning environments could increase engagement and improve learning outcomes by moving away from uniform instructional models. In the study, this position was specified through changes in students' learning behaviour: digital tutors were used not only to obtain explanations, but also for planning, progress checking and preparation for assessment. A similar issue had been addressed by H.H. Ariza (2026a), who had examined AI-powered tutoring systems capable of providing personalised guidance and assessment. Adaptive

tutoring in that study had been linked to the adjustment of instructional support to students' progress, difficulties and learning patterns. This corresponded to the findings, where Khanmigo's value was manifested in the alignment of guidance, task sequencing and feedback with the specific difficulties students encountered while preparing assignments and assessments. The benefits and limitations of this approach had been examined by W. Shoukat *et al.* (2025), who had considered AI tutors as instruments for personalised learning. Their analysis had shown that such tools could support individual learning trajectories, provide timely feedback and increase access to academic assistance, while also raising issues of technological dependence, data privacy and teacher supervision. This perspective was important for interpreting the results, since the reduction in academic stress was associated with the supplementary use of Khanmigo, Wysa and Woebot Health within independent study, rather than with the displacement of pedagogical interaction. Student evaluations showed that the AI support functions of greatest practical value were those linked to a specific learning activity: explaining the material, breaking a task down into stages, or quickly regaining concentration. General support functions received lower ratings, as did not always correspond to the student's current learning situation (Table 12).

Table 12. Students' evaluation of AI support functions following the completion of the experiment

AI support function	AI tool	Mean score (m)	Main use reported by students	Interpretation
Explanation of learning material	Khanmigo	4.61	Clarifying concepts, checking task logic, verifying written answers	Most valued function because it directly supported task completion
Step-by-step task guidance	Khanmigo	4.48	Dividing essays, coursework, presentations, and complex tasks into smaller stages	Helped students start work and reduce uncertainty about task sequence
Emotional check-ins	Wysa	4.36	Recording current emotional state, receiving short recommendations for breaks and concentration	Supported emotional self-regulation during intensive learning periods
Reflective dialogues	Woebot Health	4.29	Structuring emotional reactions after long study sessions or before assessment	Helped students identify causes of tension and prevent emotional overload
Automatic motivational messages	Khanmigo/Wysa/Woebot Health	3.71	Receiving short general encouragement during learning sessions	Less valued because generic messages were perceived as less useful than personalised recommendations

Note: ratings were made on a five-point Likert scale, where 1 indicated the minimum usefulness of a function and 5 the maximum. The data reflect the responses of students in the experimental group after eight weeks of using AI tutors and emotional support systems

Source: compiled by the author

The results also revealed differences depending on the year of study. First- and second-year students made more frequent use of the functions for explaining course material

and checking the correctness of answers. For students in higher years, tools for planning work, monitoring the progress of major projects and organising time were in greater

demand. In the final survey, 88.3% of students in the experimental group reported that were willing to continue using similar digital tools. At the same time, only 6.7% of participants noted that the use of AI had virtually no impact on how organised their studies, whilst 5.0% were undecided in their assessment. A qualitative analysis of the responses showed that the positive perception of digital tutors was not solely linked to the speed at which answers were received. Students repeatedly noted that the ability to ask a follow-up question, clarify an unclear point or have an explanation repeated without feeling any psychological discomfort contributed to greater confidence when working independently. Some participants reported that, after several weeks of using AI, turned to digital assistants less frequently with simple questions, as gradually developed their own strategies for planning their study activities. The positive perception of specific AI support functions provided a basis for identifying the factors most closely associated with reduced academic stress. This interpretation was consistent with the findings of R. Suriá-Martínez *et al.* (2025), who had examined emotional profiles and their relationship with artificial intelligence use among university students. Their study had shown that students' interaction with AI tools was related to differences in emotional characteristics and patterns of digital engagement. In the research, this perspective helped explain why emotional check-ins and reflective dialogues were among the most highly rated functions. These tools supported the recognition of tension, fatigue and uncertainty during independent study, which contributed to more deliberate regulation of learning behaviour. The functional dimension of personalised AI tutoring had also been examined by A.I. Jony *et al.* (2025), who had identified personalised feedback, adaptive guidance, progress monitoring and responses to immediate learning needs as key features of AI tutoring systems in higher education. This approach specified the results presented in Table 11. Students gave the highest ratings not to general motivational messages, but to functions directly connected with academic activity: explanation of material, step-by-step task guidance, emotional check-ins and reflective support. Therefore, the effectiveness of AI tutoring was associated with targeted support integrated into the learning process, rather than with the mere presence of digital interaction.

A regression model revealed that the reduction in academic stress was primarily linked to behavioural characteristics of AI support usage. The most noticeable changes were observed when students turned to digital tutors regularly, rather than only in situations of acute academic pressure. In such cases, Khanmigo was used for advance planning, checking the logic of task completion and preparing for assessments, whilst Wysa and Woebot Health supported short cycles of emotional self-regulation throughout the academic week. The initial level of academic stress remained a key factor. Students with higher baseline levels had greater scope for positive change, as were the ones most likely to report difficulties with concentration, procrastination and an uneven distribution of their academic workload. After

eight weeks of working with the AI tools, this group more frequently demonstrated a shift from reacting to deadlines on a case-by-case basis to more consistent planning of their study activities. The influence of trust in digital recommendations was particularly evident. Students who not only received advice from the system but also applied it in their study practice were more likely to report a more consistent pace of work, timely breaks and fewer instances of a significant backlog of tasks accumulating before the deadline. The course of study and previous experience of using AI were also significant, but their contribution was weaker compared to the regularity of interaction and the acceptance of personalised recommendations.

The model's results showed that the effectiveness of AI support was determined not by the mere fact of using digital services, but by the regularity of interaction with the system and the students' willingness to apply the recommendations received to their own learning activities. The greatest improvements were observed among participants who combined the use of Khanmigo for solving academic tasks with regular emotional check-ins on Wysa and short reflective sessions on Woebot Health. The results also helped to explain the differences between individual students who had similar initial levels of academic stress. With the same level of academic workload, better results were demonstrated by participants who used digital support as part of their day-to-day study routine, rather than merely as a means of responding to difficulties that had already arisen. The findings indicated a relationship between the systematic use of artificial intelligence tutors, emotional support functions and a reduction in academic stress. The greatest contribution was associated with personalised learning recommendations, regular emotional check-ins and self-regulation tools integrated into students' daily study routines. This conclusion may be interpreted through the framework proposed by A. ElMessiry (2025), in which a personalised artificial intelligence educational tutor had been presented as a model for customised student education. The framework had combined machine learning, natural language processing and adaptive learning algorithms to adjust educational content and learning strategies to individual students' needs. In the context of the study, this approach made it possible to clarify why the regular application of recommendations was more important than occasional access to digital tools. The reduction in academic stress was associated with the integration of AI support into students' ordinary learning behaviour, where explanations, planning prompts and self-regulatory actions were adapted to the specific difficulties encountered during independent study.

The results demonstrated a high level of agreement between algorithmic recognition of emotional state and students' self-assessments, confirming the suitability of the algorithms used for pedagogical support of the learning process. More frequent use of Khanmigo, Wysa and Woebot Health was associated with a more pronounced reduction in academic stress, academic anxiety and emotional

exhaustion. Students rated the features providing explanations of learning material, step-by-step recommendations, emotional check-ins and self-regulation tools most highly. Regression analysis confirmed that the greatest influence on the reduction of academic stress was exerted by the regularity of use of digital tutors, the initial level of academic stress and the level of trust in the recommendations of artificial intelligence systems. This made it possible to consider the combination of academic and emotional support as one of the factors enhancing the effectiveness of digital support for students in higher education institutions.

CONCLUSIONS

The study found that the sample had a balanced structure in terms of universities, study programmes, specialisms and distribution between the experimental and control groups. A total of 240 students from three universities in Spain took part in the study. Baseline measurements showed that academic stress was prevalent among a significant proportion of participants: moderate and high levels of academic stress predominated. At the same time, no statistically significant differences were found between the experimental and control groups prior to the use of AI tools, which provided a basis for further comparison of the results. After eight weeks of using Khanmigo, Wysa and Woebot Health, the experimental group showed a reduction in academic stress, study-related anxiety and emotional exhaustion. The average level of academic stress fell from 3.69 to 2.81 points, whilst in the control group it remained close to the initial value. A reduction in the proportion of students experiencing high levels of stress and an increase in satisfaction with the learning process were

also observed. According to the participants' responses, these positive changes were linked to the ability to obtain explanations of the course material more quickly, plan the completion of assignments, check progress, and use brief emotional self-regulation tools.

Mood recognition algorithms demonstrated a sufficient level of correlation with students' self-assessments, particularly when identifying states of calm, tension and fatigue. Regular use of AI support was associated with a more pronounced reduction in academic stress. Students rated the functions for explaining learning material, step-by-step recommendations, emotional check-ins and brief reflective dialogues most highly. Regression analysis showed that the strongest associations with reduced academic stress were the regularity of digital tutor use, the initial level of stress and trust in the recommendations of artificial intelligence systems. The results confirmed the pedagogical value of combining academic and emotional AI support within a university educational setting. Prospects for further research include expanding the sample size, extending the duration of observation, and comparing the effectiveness of different AI tutor models and emotional state recognition algorithms within the context of university education.

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REFERENCES

- [1] Aguado-García, J.-M., Alonso-Muñoz, S., & De-Pablos-Herederó, C. (2025). Using artificial intelligence for higher education: An overview and future research avenues. *SAGE Open*, 15(2). doi: 10.1177/21582440251340352.
- [2] American Sociological Association. (2025). *Code of ethics*. Retrieved from <https://surl.li/fociya>.
- [3] Ariza, H.H. (2026a). *Advancing AI-powered tutoring systems: Institutional scaling, data-informed pedagogy, and responsible integration in higher education*. *Clareus Scientific Science and Engineering*, 3(3), 35-40.
- [4] Ariza, H.H. (2026b). Implementing AI-powered tutoring systems to enhance personalized learning in higher education. In D. Guralnick, M.E. Auer & A. Poce (Eds.), *Proceedings of "The learning ideas conference" 2025: Creativity and new technologies in learning for the workplace and higher education* (pp. 351-363). Cham: Springer. doi: 10.1007/978-3-032-09908-2_26.
- [5] Baillifard, A., Gabella, M., Banta Lavenex, P., & Martarelli, C.S. (2025). Effective learning with a personal AI tutor: A case study. *Education and Information Technologies*, 30(1), 297-312. doi: 10.1007/s10639-024-12888-5.
- [6] ElMessiry, A. (2025). Personalized AI educational tutor: A framework for customized student education. In *INTED2025 proceedings: 19th international technology, education and development conference* (pp. 3608-3612). Valencia: IATED. doi: 10.21125/inted.2025.0911.
- [7] European Commission. (2021). *Ethics and data protection*. Retrieved from <https://surl.li/eijden>.
- [8] Flores Limo, F.A., et al. (2023). *Personalized tutoring: ChatGPT as a virtual tutor for personalized learning experiences*. *Przestrzeń Społeczna (Social Space)*, 23(1), 292-312.
- [9] Galindo-Domínguez, H., Delgado, N., Losada, D., & Etxabe, J.-M. (2024). An analysis of the use of artificial intelligence in education in Spain: The in-service teacher's perspective. *Journal of Digital Learning in Teacher Education*, 40(1), 41-56. doi: 10.1080/21532974.2023.2284726.
- [10] Gallastegui, L.M.G., & Forradellas, R.R. (2024). Optimization of the educational experience in higher education using predictive artificial intelligence models. *Revista de Gestão Social e Ambiental*, 18(5), article number e07111. doi: 10.24857/rgsa.v18n5-104.
- [11] González-Rico, P., & Lluch Sintés, M. (2024). Empowering soft skills through artificial intelligence and personalised mentoring. *Education Sciences*, 14(7), article number 699. doi: 10.3390/educsci14070699.

- [12] Gurung, A., Lin, J., Gutterman, J., Thomas, D.R., Houk, A., Gupta, S., Brunskill, E., Branstetter, L., Alevan, V., & Koedinger, K. (2025). Human tutoring improves the impact of AI tutor use on learning outcomes. In A.I. Cristea, E. Walker, Y. Lu, O.C. Santos & S. Isotani (Eds.), *Artificial intelligence in education: 26th international conference, AIED 2025* (pp. 393-407). Cham: Springer. doi: [10.1007/978-3-031-98459-4_28](https://doi.org/10.1007/978-3-031-98459-4_28).
- [13] Hajeer, A., Papp-Váry, Á., & Pólya, É. (2024). AI tutors vs. human instructors: Perceptions of higher education students in Hungary and Spain. *EduTec: Revista Electrónica de Tecnología Educativa*, 89, 105-120. doi: [10.21556/edutec.2024.89.3523](https://doi.org/10.21556/edutec.2024.89.3523).
- [14] Hernández-Herrera, J.R., Ortiz-Bejar, J., & Ortiz-Bejar, J. (2026). Adaptive and personalized learning in higher education: An artificial intelligence-based approach. *Education Sciences*, 16(1), article number 109. doi: [10.3390/educsci16010109](https://doi.org/10.3390/educsci16010109).
- [15] ICC/ESOMAR International Code of Conduct for Market, Public and Social Research and Data Analysis. (2025, July). Retrieved from <https://standards.esomar.org/assets/documents/icc-esomar-code-2025.pdf>.
- [16] Javed, S., e Zehra, S.R., Ullah, H., & Naveed, M. (2025). How AI can detect emotional cues in students, improving virtual learning environments by providing personalized support and enhancing social-emotional learning. *Review of Applied Management and Social Sciences*, 8(1), 643-660. doi: [10.47067/ramss.v8i1.500](https://doi.org/10.47067/ramss.v8i1.500).
- [17] Jony, A.I., Lara Navarra, P., & Serradell-López, E. (2025). Key functionalities of personalized AI tutoring systems that boost learning outcomes in higher education. In *ICERI2025 proceedings: 18th annual international conference of education, research and innovation* (pp. 8200-8209). Seville: IATED. doi: [10.21125/iceri.2025.2292](https://doi.org/10.21125/iceri.2025.2292).
- [18] Kestin, G., Miller, K., Klales, A., Milbourne, T., & Ponti, G. (2025). AI tutoring outperforms in-class active learning: An RCT introducing a novel research-based design in an authentic educational setting. *Scientific Reports*, 15, article number 17458. doi: [10.1038/s41598-025-97652-6](https://doi.org/10.1038/s41598-025-97652-6).
- [19] Khanmigo. (n.d.). Retrieved from <https://www.khanmigo.ai>.
- [20] Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. *Frontiers in Psychology*, 16, article number 1498132. doi: [10.3389/fpsyg.2025.1498132](https://doi.org/10.3389/fpsyg.2025.1498132).
- [21] López-Goyez, J.P., González-Briones, A., & Chamorro Villarreal, A.F. (2024). Intelligent tutoring systems in smart learning environments for higher education: A systematic literature review. In C. Herodotou, S. Papavlasopoulou, C. Santos, M. Milrad, N. Otero, P. Vittorini, R. Gennari, T. Di Mascio, M. Temperini & F. De la Prieta (Eds.), *Methodologies and intelligent systems for technology enhanced learning, 14th international conference* (pp. 265-276). Cham: Springer. doi: [10.1007/978-3-031-73538-7_24](https://doi.org/10.1007/978-3-031-73538-7_24).
- [22] Mehrad, A., Tahriri Zangeneh, M.H., Bouzedif, M., & Rweramila, N.G. (2025). Educational stress and artificial intelligence tools: A study of international students' experiences in Spanish higher education. *Journal of Asian Social Science Research*, 7(1), 1-32. doi: [10.15575/jassr.v7i1.127](https://doi.org/10.15575/jassr.v7i1.127).
- [23] Pratama, M.P., Sampelolo, R., & Lura, H. (2023). Revolutionizing education: Harnessing the power of artificial intelligence for personalized learning. *Klasikal: Journal of Education, Language Teaching and Science*, 5(2), 350-357. doi: [10.52208/klasikal.v5i2.877](https://doi.org/10.52208/klasikal.v5i2.877).
- [24] Rodríguez Cairo, D., & Ramírez Echavarría, Y. (2023). Smart tutors: Improving the quality of higher education through AI. *LatIA*, 1, article number 8. doi: [10.62486/latia20238](https://doi.org/10.62486/latia20238).
- [25] Sajja, R., Sermet, Y., Cikmaz, M., Cwierty, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, 15(10), article number 596. doi: [10.3390/info15100596](https://doi.org/10.3390/info15100596).
- [26] Sari, H.E., Tumanggor, B., & Efron, D. (2024). Improving educational outcomes through adaptive learning systems using AI. *International Transactions on Artificial Intelligence*, 3(1), 21-31. doi: [10.33050/italic.v3i1.647](https://doi.org/10.33050/italic.v3i1.647).
- [27] Shoukat, W., Rizwan, N., & Khan, M.T. (2025). [The role of artificial intelligence \(AI\) tutors in personalized learning: Benefits and challenges](https://doi.org/10.33050/italic.v3i1.647). *Journal of Social Signs Review*, 3(4), 1-13.
- [28] Sornavalli, G., Nair, S.M., Vardharajan, S., & Srinivasan, S. (2025). The AI tutor: Revolutionizing education through personalized learning. In C.S. Joice & M. Selvi (Eds.), *Pedagogical revelations and emerging trends* (pp. 1-8). London: CRC Press. doi: [10.1201/9781003587538-1](https://doi.org/10.1201/9781003587538-1).
- [29] Suriá-Martínez, R., García-Castillo, F., López-Sánchez, C., & García del Castillo, J.A. (2025). Emotional profiles and their relationship with the use of artificial intelligence in university students. *Behavioral Sciences*, 15(11), article number 1573. doi: [10.3390/bs15111573](https://doi.org/10.3390/bs15111573).
- [30] Vaca Zambrano, S.E., Machado Herrera, P.H., Huera Paltán, B.P., & Farez Atencia, J.C. (2025). Implementation of artificial intelligence for personalized learning in higher education. *Health, Science and Technology – Lecture Series*, 4, article number 1436. doi: [10.56294/sctconf20251436](https://doi.org/10.56294/sctconf20251436).
- [31] Woebot Health. (n.d.). Retrieved from <https://woebothealth.com/>.
- [32] Wysa. (n.d.). Retrieved from <https://www.wysa.com/>.
- [33] Zafar, Q., Kiren, A., & Naz, Z. (2026). The role of artificial intelligence in supporting students' emotional regulation and learning anxiety. *The Critical Review of Social Sciences Studies*, 4(1), 589-600. doi: [10.59075/884gdn98](https://doi.org/10.59075/884gdn98).
- [34] Zhang, X., Wong, S.Y., & Cheah Soon Lee, K. (2025). Effectiveness of AI-powered tutoring systems in enhancing learning outcomes. *Eurasian Journal of Educational Research*, 116, 143-172. doi: [10.14689/ejer.2025.116.09](https://doi.org/10.14689/ejer.2025.116.09).
- [35] Zong, Y., & Yang, L. (2025). How AI-enhanced social-emotional learning framework transforms EFL students' engagement and emotional well-being. *European Journal of Education*, 60(1), article number e12925. doi: [10.1111/ejed.12925](https://doi.org/10.1111/ejed.12925).