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Understanding University Students' Intentions to Use Chatbots in Computer Programming Education: A Quantitative Study

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Abstract: Recently, the use of artificial intelligence in education is one of the more frequently discussed issues by researchers. Especially the use of artificial intelligence applications called chatbots or artificial intelligence language models in education is increasing day by day. Although the use of chatbots in education is possible for every course, it is observed that students intend to use chatbots as an assistant, an instructor, or a guide, especially in computer programming courses, which are difficult to learn and have complex structures. In this context, the aim of this study is to examine the intention of university students taking computer programming courses to use chatbots in their education. The participants consisted of 413 university students studying at a state university and taking a "computer programming" course in the 2023-2024 academic year. Descriptive statistics, independent sample t-test and one-way analysis of variance (ANOVA) were used to analyze the data. Results have shown that university students indeed possess intentions to use chatbots in computer programming education and this intention is mostly motivated by the performance expectation towards the course. In addition, for the purposes of using chatbots in computer programming education; conceptual understanding, identifying errors in program code and looking up for correct syntactical rules were among the most prominent reasons. In terms of independent variables, while there was no difference in terms of department, income status, device using chatbots, and the role attributed to chatbot by the student, a significant difference was found in terms of gender, grade level, use experience and frequency of chatbots use. According to the study, university students studying programming plan to use chatbots powered by artificial intelligence, and the usage of chatbots in programming education is expected to grow over time in tandem with the advancement of AI technology.

Keywords: Artificial Intelligence, AI, Chatbot, Higher Education, Survey Research

1. Introduction

Today, with the rapid advancement of technology, digital transformations are expected in the field of education. Recently, one of the most important elements of this transformation is the use of artificial intelligence-based systems in education and the integration of artificial intelligence language model supported chatbots into educational processes (Verleger & Pembrige, 2018; Yildiz-Durak, 2023). Artificial intelligence integration in education is increasingly manifesting through various applications (Raffaghelli et al., 2022; Rahman & Watanobe, 2023). Dialogue education systems, chatbots, data mining in education, article analysis of students, experiential education, education for children with special needs, intelligent agents, child and robot interaction, artificial intelligence-based assessment systems, automatic test creation systems can be given as examples of these applications (Holmes et al., 2023). On November 30, 2022, Open AI released ChatGPT, an artificial intelligence language model with functionality in a few areas, including education, coding, creative writing, information research, and general conversation (Gill & Kaur, 2023). In addition, with this artificial intelligence language model, tasks such as answering questions, providing information, producing creative content, and explaining complex concepts have started to be fulfilled in a very short time. ChatGPT, which is the most interesting and increasingly used chatbot application of recent times, has more than one million users as of today (Keles, 2023).

A chatbot is a software program that can communicate with humans through natural language. This term, created by combining the words "chat" and "robot", describes artificial intelligence systems designed to assist humans, usually through text-based or voice dialogues (Luo et al., 2022). Chatbots are

applications that have the potential to help students better understand the subjects they do not understand by providing an interactive learning experience. Chatbots also provide students with personalised and interactive learning experiences by using artificial intelligence sub-disciplines such as natural language processing and machine learning (Kerlyl et al., 2006). In particular, the rising trend of technology in the field of education, the integration of artificial intelligence and chatbot technologies into teaching methodologies opens new horizons for educators and students, especially in challenging courses. In courses such as computer programming, chatbots have been claimed to support students with teaching, mentoring, and assisting roles (Moon et al., 2023). Programming or coding courses can be quite challenging for students with their complex, abstract and dynamic concepts (McCracken et al., 2001; Qian & Lehman, 2017). In this context, it is argued that integrating artificial intelligence into the classroom can be useful in helping students learn abstract ideas such as programming and algorithmic thinking. In parallel with the idea that the use of artificial intelligence in overall educational efforts will reduce the cognitive load of students (Fryer et al., 2020), it is also thought that the use of such applications in programming education might also help students reduce the high cognitive load encountered by students in programming courses. In a study by Okonkwo and Ade-Ibijola (2020), a chatbot system called Python-Bot was presented to novice programmers. As a result of the use of this system, it was stated that most students taking Python programming courses and students who had previously completed a Python programming course agreed that this tool was user-friendly, simplified the task of internalizing programming logic and improved Python programming skills overall. Biswas (2023) emphasised that ChatGPT offers a wide range of capabilities for computer programming, including code completion, correction, prediction, error correction, optimisation, document generation, chatbot development, text-to-code conversion and increases the productivity of programmers. Similarly, Surameery and Shakor (2023) mention the capabilities of ChatGPT in providing debugging assistance, error prediction and error explanation to help solve programming problems. As can be seen from the related literature, the benefits of using chatbots in programming education and the capabilities of chatbots are discussed. However, in addition to the benefits that chatbots use can bring to education, students' intentions, and acceptance for the use of new technologies such as chatbots in education gain importance.

The use of technology in education, especially in the case of new tools such as chatbots, has been studied using various theoretical models to understand how individuals' approach and adopt these technologies. These models have an important role in elucidating users' behaviours and expectations towards these behaviours, especially the influence of personal factors. For example, the Unified Theory of Acceptance and Use of Technology (UTAUT), which was developed by Venkatesh et al. (2003), identifies four main elements and four moderating factors to explain how individuals accept and use new technologies. These are (a) performance expectancy, (b) effort expectancy, (c) social influence and (d) facilitating conditions. Age, gender, experience, and education are considered as moderators. Each of these factors can change the effect of the four main factors mentioned above. The UTAUT model has been frequently used to analyse technology acceptance in a wide range of fields (Dwivedi et al., 2011), especially in the field of education. The results of the study by Raffaghelli et al. (2022) showed that the UTAUT model is a valid and widely used model for analysing technology acceptance in many fields, including education. Recent studies have found that the UTAUT model is also effective in evaluating the acceptance of technologies such as chatbots (Williams et al. 2015; Kim et al., 2019).

The rapid progress of technological developments necessitates the adaptation of individuals to rapid changes to commence as smoothly as possible. As Teo et al. (2019) emphasized, individuals' intentions to accept technology play a critical role in successfully integrating these developments into society. Based on this information, it can be said that one of the prerequisites for university students to encourage the use of new technologies such as chatbots is technology acceptance and intention. This is

especially true in a difficult domain such as computer programming education, which comprise a high demand technical skill that holds promise for both individuals and for nations when learned properly. Under these circumstances, the acceptance and intention of university students towards use of AI chatbots in education gain greater importance. In a developing country like Turkey, it is essential to determine the moderator variables that affect technology acceptance in education, understand students' intentions to use chatbots, and create scenarios for integrating chatbots into education. This study aims to contribute to the literature by examining university students' intentions regarding the use of artificial intelligence in education. Specifically, it aims to examine the intention of university students taking computer programming courses to use chatbots in education. The study seeks answers to the following research questions:

1. What is the level of chatbot use intention of university students taking computer programming courses?
2. For what purposes do university students taking programming education courses use chatbots in their education?
3. Do the intention of university students taking computer programming courses towards using chatbots in education vary according to the following independent variables?
 - a. Gender,
 - b. Department,
 - c. Grade level,
 - d. Parental income status,
 - e. Chatbot use experience,
 - f. Device used for chatbot access,
 - g. Frequency of chatbot use,
 - h. Role attributed to chatbot by the student.

2. Methodology

In this study, which was conducted to examine the intention of university students taking computer programming courses to use chatbots in education in terms of various variables, a quantitative descriptive method was used. Descriptive methods are used in studies in which the views of the participants on a subject or event or their interests, skills, abilities, attitudes, etc. are determined, and which are generally conducted on larger samples than other studies (Buyukozturk et al., 2008). In this study, the quantitative descriptive method was used to determine the intention of university students taking computer programming courses to use chatbots in education and to determine whether this intention differs according to certain variables.

2.1. Participants

The participants of the study consisted of 413 university students taking computer programming courses in Computer Engineering, Mechanical Engineering and Econometrics departments at a state university during the 2023-2024 academic year. It was determined that 121 (29.3%) of the participants were female and 292 (70.7%) were male students. The average age of the university students was found to be $M=20.30$. Table 1 shows all demographic information of the participants.

Table 1*Frequency-Percentage Data of the Participants*

Variables	N	%
Gender		
Female	121	29.3
Male	292	70.7
Department		
Computer Engineering	238	57.6
Mechanical Engineering	140	33.9
Econometrics	35	8.5
Grade level		
1st grade	163	39.5
2nd grade	128	31.0
3rd grade	64	15.5
4th grade	58	14.0
Parental Income status		
11.000- 20.000 TL	132	32.0
21.000- 30.000 TL	127	30.8
31.000- 40.000 TL	84	20.3
40.000 TL and above	70	16.9
Prior Chatbot Use Experience		
Yes	295	71.4
No	118	28.6
Chatbot Type Used		
Chat GPT	270	65.4
Copilot	12	2.9
Google Bard	11	2.7
Tabnine AI	2	0.4
Not using	118	28.6
Device Used for Chatbot Access		
Smartphone	94	22.8
Computer	201	48.7
Not using	118	28.6
Frequency of Chatbot Use (Weekly)		
1-10 times	177	42.9
11-20 times	70	16.9
21-30 times	48	11.6
Not using	118	28.6
Role Attributed to Chatbot		
Assisting	190	46.0
Learning	128	31.0
Mentoring	95	23.0
Total Participants	413	100.0

2.2. Data collection tools

A survey form was developed by the researchers as a data collection tool in the study. The research form consists of two parts. The first part includes demographic data (gender, age, department, grade level, and income status etc.) and information about chatbots usage (prior chatbots use experience, type

of chatbots used, frequency of chatbots use, device used for chatbot access, and role attributed to chatbots etc.) and the second part includes the intention to use chatbots in education scale.

Behavioural Intention Scale for Using and Learning Chatbot in Education. The adaptation of the "Behavioural Intention to Use and Learn Chatbot Scale" developed by Mokmin and Ibrahim (2021) into Turkish was conducted by Yildiz Durak and Onan (2023). The scale adapted to Turkish consists of 24 items and 8 sub-dimensions. The scale is 7-point Likert type. Cronbach α internal consistency coefficient of the scale was calculated as 0.96. Cronbach α internal consistency coefficient for performance expectancy factor was 0.91, 0.92 for effort expectancy, 0.91 for attitude towards improving learning, 0.86 for social influence, 0.84 for facilitating conditions, 0.90 for self-efficacy, 0.89 for anxiety, 0.92 for behavioural intention to use/learn **chatbots**. Finally, the fit indices of the scale **were** [$\chi^2(224) = 871.50, \chi^2/df = 3.89, RMSEA = 0.063, GFI = 0.91, NFI = 0.99, NNFI = 0.99, CFI = 0.99, IFI = 0.99$]. In this study, the Cronbach α internal consistency coefficient of the behavioural intention to use/learn chatbots factor was calculated as 0.89.

2.3. Data collection and analysis process

In the study, the data collection process lasted for one month during January in the autumn term of the 2023-2024 academic year. Before starting the data collection process, ethics committee approval was obtained with the decision numbered 01/23 taken at the meeting of Trakya University Social and Human Sciences Research Ethics Committee dated 24.01.2024 (Number: E-29563864-050.04-589075). Data were collected both online and face-to-face by the researchers. It took approximately 10 minutes to fill out a research form. Firstly, the participants were informed about the research, and it was explained that participation in the research was voluntary. Before analysing the data, normality assumption was tested. According to the results of the Kolmogorov-Smirnov test, it was determined that the data were normally distributed ($p = .07$). In addition, Levene's test was performed to check the homogeneity assumption. As a result of the test, it was seen that the homogeneity assumption was met in terms of department, grade level, parental income status and frequency of chatbots use variables ($p > .05$). For this reason, parametric tests were used to analyse the data. In this respect, descriptive statistics, independent sample t-test and one-way analysis of variance (ANOVA) were used in the study. The effect size of the analysis results was also calculated in the study using the eta square coefficient.

3. Findings

In the study, the findings are explained in the order of the research questions and by giving direct research questions.

3.1. What is the level of chatbots use intention of university students taking computer programming course?

In this quantitative study examining the intention to use chatbots in education of university students taking computer programming course, the average score obtained from the intention to use/learn chatbots in education was $M = 5.47$. When the mean scores of the other sub-factors of the scale were examined, performance expectation as $M = 5.29$, effort expectation as $M = 5.10$, attitude towards improving learning as $M = 4.83$, social influence as $M = 3.42$, facilitating conditions as $M = 4.44$, self-efficacy as $M = 4.73$, anxiety as $M = 2.45$ were determined. Table 2 shows the descriptive statistics of the scale and its sub-factors.

Table 2*Descriptive Statistics of the Scale and Its Sub-Factors*

Scale and Sub Dimensions	N	Min	Max	Mean	Std. Dev.
1.Performance expectation	413	1.00	7.00	5.29	1.240
2.Effort expectation	413	1.00	7.00	5.10	1.308
3.Attitude towards improving learning	413	1.00	7.00	4.83	1.326
4.Social Influence	413	1.00	7.00	3.42	1.605
5.Facilitating conditions	413	1.00	7.00	4.44	1.292
6.Self-efficacy	413	1.00	7.00	4.73	1.610
7.Anxiety	413	1.00	7.00	2.45	1.340
8.Behavioral intention to use/learn chatbot	413	1.00	7.00	5.47	1.322

When Table 2 is examined, it is seen that the behavioural intention and performance expectation levels of university students towards using/learning chatbots in education are at a high level, their intention to use chatbots in education in terms of anxiety and social influence factors is at a low level, and other factors are at a medium level. As a result of these findings, it can be concluded that university students intend to use chatbots in computer programming education.

3.2. What are the purposes of using chatbots in programming education of university students taking computer programming course?

When the purposes of using chatbots in the education of university students taking programming courses were examined, it was seen that there were basically 6 purposes of their use. It was observed that 290 (98.3%) of the students who used chatbots in programming education used chatbots to learn the subject related to programming. Following this, 282 (95.6%) of the students use chatbots to find and debug code errors in programming. Table 3 shows the purposes of using chatbots in programming education of university students.

Table 3*Scenarios of Chatbots Usage Purposes in Computer Programming Education*

Purpose of Using Chatbots in Programming Education*	N	%
Conceptual learning about programming	290	98.3
Code error detection and debugging (Debug)	282	95.6
Reference material about syntactical rules (Syntax)	255	86.4
Analysing the codes of homework and in-class exercises	247	83.7
Preparing for programming exams	161	54.6
Creating another programming examples without exercise in course	146	49.5

* The number of university students using chatbots in Computer Programming education was determined as 295 (100%). However, since more than one option can be selected for the purpose of

using chatbots in education in the research form created to collect data in the study, this number exceeds 295. In this respect, the total number of university students is not included in the table.

When Table 3 is examined, it is seen that university students primarily use chatbots in programming education to learn certain conceptual topics and to find errors in code writing. This result shows that chatbots support students in learning at their own pace and provide advantages in terms of personalised learning. Following this, it was also found that students used chatbots as a reference material for the syntax of programming language codes. Thus, it is seen as valuable in terms of time that students can quickly access information in terms of programming from anywhere at any time. Finally, it was revealed that students used chatbots to analyse the program codes they did in the lessons or assigned homework, but they used chatbots less frequently to prepare for exams or to produce new programming research. These findings suggest some positive effects or concerns in terms of deep or surface learning approaches in programming education for university students.

3.3. Do the chatbots usage intentions of university students taking programming courses vary according to gender?

An independent sample t-test was conducted to determine whether there is a difference in terms of gender in the intention to use Chatbot in education of university students taking computer programming courses. As a result of the test, there was a significant difference between male and female university students in terms of their intention to use chatbots in education ($p=.04$). According to finding, Male's intention to use chatbots in education is higher than female. Table 4 shows the results of the independent sample t-test analysis.

Table 4

Independent Sample T-Test According to Gender

Gender	N	Mean	Std. Dev.	df	t	p	Effect size
Female	121	5.27	1.323	411	-2.016	.04*	.01
Male	292	5.56	1.314				

* Significance at .05 level

3.4. Do the chatbots usage intentions of university students taking computer programming course vary according to the department?

One-way analysis of variance (ANOVA) was performed to determine whether there is a significant difference in the Chatbot usage intentions of university students taking computer programming courses according to the department of study. As a result of the ANOVA test, no significant difference was found between the student groups in terms of the department of education ($p=.13$). The results of the analysis are shown in Table 5.

Table 5

ANOVA Analysis Results According to the Department

	Sum of squares	df	Mean of squares	F	p
Between groups	7.223	2	3.611	2.077	.13
Within groups	713.058	410	1.739		
Total	720.281	412			

3.5. Do the chatbots usage intentions of university students taking computer programming education vary according to the grade level?

ANOVA analysis was performed to examine whether the chatbots usage intentions of university students taking Computer Programming courses vary significantly according to the grade level. As a result of ANOVA analysis, a significant difference was found between student groups in terms of class level ($p=.00$). Tukey which is one of the post-hoc test was used to investigate the differences between groups. According to findings, 1st grade students' intention to use chatbots in education ($M=5.69$) is higher than 2nd ($M=5.26$) and 3rd ($M=5.17$) grade students. The results of the analysis are shown in Table 6.

Table 6

ANOVA Analysis Results According to Grade Level

Grade level	N	Mean	Std. Dev.	df	F	p	Difference	Effect size
1 st grade	163	5.69	1.223	3 409	4.238	.00**	1>2, 1>3	.03
2 nd grade	128	5.26	1.335					
3 rd grade	64	5.17	1.364					
4 th grade	58	5.67	1.402					

** Significance at .01 level

3.6. Do the chatbots usage intentions of university students taking computer programming courses vary according to income status?

ANOVA analysis was performed to examine whether the chatbots usage intentions of university students taking Computer Programming courses differ according to income status. As a result of the analysis, no significant difference was found between the student groups in terms of income status ($p=.97$). The results of the analysis are shown in Table 7.

Table 7

ANOVA Analysis Results According to Income Status

	Sum of squares	df	Mean of squares	F	p
Between groups	.146	3	.049	.028	.97
Within groups	720.136	409	1.761		
Total	720.281	412			

3.7. Do the chatbots usage intentions of university students taking computer programming course vary according to their chatbots use experience in education?

Independent sample t-test was conducted to test whether the Chatbot usage intentions of university students taking Computer Programming course vary according to the experience of using chatbots in education. According to the results of the independent sample t-test, a significant difference was found between the student groups ($p=.00$). It was concluded that the significant difference obtained was in favour of university students ($M=5.58$) who had previous experience of using Chatbot in education. Table 8 shows the results of the analysis.

Table 8*Independent Sample T-Test According to Prior Chatbots Use Experience*

Chatbot use experience	N	Mean	Std. Dev.	df	t	p	Effect Size
Yes	295	5.58	1.272	411	2.668	.00**	.02
No	118	5.20	1.410				

*** Significance at .01 level*

3.8. Do the chatbots usage intentions of university students taking computer programming course vary according to their device used for chatbots?

Independent sample t-test was conducted to test whether the Chatbot usage intentions of university students taking Computer Programming course vary according to the device using chatbots in education. According to the results of the independent sample t-test, a significant difference was not found between the student groups ($p=.71$). Table 9 shows the results of the analysis.

Table 9*Independent Sample T-Test According to Device Used for Chatbots*

Chatbot use experience	N	Mean	Std. Dev.	df	t	p
Smartphone	94	5.53	1.378	293	-.378	.71
Computer	201	5.58	1.227			

*** Significance at .01 level*

3.9. Do the chatbots usage intentions of university students taking computer programming courses differ according to the frequency of chatbots use?

In order to examine whether the chatbots usage intentions of university students taking Computer Programming courses vary according to the frequency of chatbots usage, ANOVA analysis was performed on the sample of university students who had previous chatbots usage experience. As a result of the analysis, a significant difference was found between the student groups in terms of the frequency of chatbots use in education ($F(2, 292) = 11.767$; $p=.00$). Tukey HSD test, one of the post-hoc tests, was applied to test between which groups the significant difference was between. According to the results of the test, the intention to use chatbots in computer programming education is significantly lower among university students who use chatbots 1-10 times ($M=5.34$) a week for computer programming education than those who use chatbots 21-30 times ($M=6.31$). In addition, the intention to use chatbots in education of university students who use chatbots 11-20 times ($M=5.63$) weekly for computer programming education is significantly lower than those who use chatbots 21-30 times ($M=6.31$). The results of the analyses are shown in Table 10.

Table 10*ANOVA Analysis Results According to the Frequency of Chatbots Use*

Frequency of chatbots use (Weekly)	N	Mean	Std. Dev.	df	F	p	Difference	Effect size
1-10 times	177	5.34	1.317	292	11.767	.00**	3>1, 3>2	.06
11-20 times	70	5.63	1.215					
21-30 times	48	6.31	.870					

*** Significance at .01 level*

3.10. Do the Chatbot usage intentions of university students taking computer programming courses vary according to role using chatbots?

ANOVA analysis was performed to examine whether the chatbots usage intentions of university students taking Computer Programming courses differ according to role using chatbots. As a result of the analysis, no significant difference was found between the student groups in terms of the role using chatbots ($p=.73$). The results of the analysis are shown in Table 11.

Table 11

ANOVA Analysis Results According to Role Attributed to Chatbot by the Student

	Sum of squares	df	Mean of squares	F	p
Between groups	1.091	2	.546	.311	.73
Within groups	719.190	410	1.754		
Total	720.281	412			

4. Discussion and Conclusions

This study was conducted to examine the intention of university students taking programming courses to use chatbots in education in terms of certain variables. When the mean scores of the sub-factors of the intention to use chatbots in education scale of university students were examined, it was found that the performance expectation had a mean score of 5.29, the effort expectation had a mean score of 5.10, and the behavioural intention to use/learn chatbots had a mean score of 5.47. As a result of the findings, it was seen that university students' behavioural intentions towards using/learning chatbots in computer programming education were positive. In addition, it was also observed that university students were not highly concerned about the use of chatbots in education. This finding supports the behavioural intention of university students in terms of chatbots use in education. Supporting the findings of the study, in a study conducted in Hong Kong with the participation of 399 undergraduate and graduate students from various disciplines, it was stated that there was a generally positive attitude towards the use of ChatGPT in teaching and learning. In addition, students also expressed concerns about accuracy, privacy, ethical issues, and the impact on personal development, career prospects, and social values in terms of their intentions to use chatbots in education (Chan & Hu, 2023). In a study conducted by Topal et al. (2021), it was stated that students expressed positive opinions about chatbots in terms of use in education because they received feedback from the chatbots they used in education and subjectively saw them as exciting and fun learning objects. In another study conducted by Aktay et al. (2023), it was revealed that students' attitudes towards the use of ChatGPT in science education were high and they found the use of ChatGPT in science education fun. In conclusion, in line with the relevant literature and the findings of this study, it can be said that students' intentions to use chatbots in education in different courses and in different educational roles are positive.

When the purposes of using chatbots in the education of university students taking programming courses were examined, it was seen that there were basically six purposes of use. It was observed that students who used chatbots in computer programming education mostly used chatbots to learn the subject related to programming by gaining conceptual understanding. Following this, it was observed that students used chatbots to find errors in program codes, to access reference material for proper syntax rules, to do exercises and homework assignments in the classroom, to prepare for exams and to develop questions for practice. In one of the rare recent studies that examined this relatively new phenomenon, the opinions of university students on the use of ChatGPT in programming education were examined. According to student opinions, it was stated that ChatGPT was used in programming education in terms of providing fast and mostly correct answers to questions, improving thinking skills, facilitating debugging, and increasing self-confidence (Yilmaz & Yilmaz, 2023). In another study, it was

stated that ChatGPT in programming education provides assistance in debugging errors in codes and can also play a role in solving programming errors by providing error prediction and error explanation (Surameery & Shakor, 2023). Another study investigating the use of ChatGPT in Python programming language education similarly shows that ChatGPT assisted students as an assistant and that using ChatGPT as a programming aid yielded better results than working without any external assistance. Furthermore, the help provided by ChatGPT increased students' coding proficiency, improved the quality of their explanations, and deepened their understanding of standard solution methods (Vukojić & Krstić, 2023). As a result of the findings obtained, it is thought that the use of chatbots in computer programming education will become widespread in programming over time due to the potential of using chatbots in computer programming education and the large number of training scenarios.

The study revealed that the chatbots usage intentions of university students in computer programming education differed according to the gender variable. According to the finding, it was determined that male students have significantly higher chatbots usage intentions in programming education than female students. Supportingly, in UNESCO's report in 2019, it was stated that there is a difference between genders in the adoption of new technologies and that men are generally interested in new technologies earlier than women (West et al., 2019). In the report, this situation was attributed to factors such as self-efficacy and educational differences in technological disciplines. In parallel to this, in this study, this situation can be attributed to the higher self-efficacy and interest of male students in a course such as programming education, which includes complex and difficult dynamics, and programming skills. Another study focused on the use of chatbots by men and women four months after the release of ChatGPT. The results of this study similarly show that women are less likely to use chatbots than men in terms of technology use and acceptance in terms of gender (Draxler et al., 2023). In addition to these findings, it is possible to come across studies in which there is no difference in intention between men and women in terms of chatbots use in programming education (Malik et al., 2022).

The analysis indicated that the chatbot usage intentions of university students in computer programming education did not differ according to the department variable. In the study, there are Computer Engineering, Mechanical Engineering and Econometrics departments. While programming courses are available almost every semester in the Computer Engineering department, there is only one semester of C programming course in the Mechanical Engineering and Econometrics departments. This means that students in Mechanical Engineering and Econometrics are more novice in programming. However, since it is thought that novices have a higher cognitive load in a programming course, that is, they have greater difficulty in learning, it is thought that their intention to use chatbots would be higher. In support of this, Okonkwo and Ade-Ibijola (2020) showed that a chatbots containing the basic syntactic structures and semantics of Python programming language helped novice programmers to learn python programming language. Similarly, in another study, it was stated that chatbots support students in learning programming in terms of course information, course-specific resources, explanation of basic programming concepts and answers to programming-related questions (Verleger & Pembridge, 2018). In addition, it is an expected result that computer engineering students have a higher level of desire and obligation to follow advanced technologies and technological developments compared to other departments. Therefore, the fact that there is no difference according to the department in the study is an explainable result. In future studies, studies on why students in different departments use chatbots according to their approaches such as surface and deep learning will reveal the basis of the intention to use chatbots in education.

The study found that the chatbot usage intentions of university students in computer programming education differed according to the grade variable. First grade university students' intention to use chatbots in programming education is significantly higher. In addition, although no significant difference

was obtained, it is seen that the average scores of the students studying in the fourth grade from the scale of intention to use chatbots in education are high. As a result of the findings, it can be said that first and fourth grade students have higher intention to use chatbots in programming education. In the study, it is an expected result that first graders have high intention to use chatbots in education. Because it is known that students who are new to computer programming have difficulties in subjects such as programming topics, syntax and problem solving (Iqbal et. al, 2021; Malik et al., 2022). It is already expected that university students who have a high cognitive load in programming education (Şişman & Küçük, 2018) will tend to use assistive technologies, even for purposes such as passing the programming course or learning programming. However, the high intention of fourth grade university students to use chatbots in education can be attributed to the fact that all fourth graders are from the computer engineering department. Because the fourth-year students in the computer engineering department are in a rush to finish school, their desire to finish school with a higher score, their more experienced in education and programming, and their desire for deep learning in order to show that they are sufficient in terms of programming in job applications have the potential to cause this.

It was found that the chatbot usage intentions of university students in computer programming education did not differ according to income status. In the related literature, there is no study in which the income status variable is used, but it is thought that the free versions of chatbots and the ease of access of students to these versions are factors in obtaining this finding. However, in future studies, differences between student groups in terms of lack of internet and technological devices in terms of access to chatbots and differences between student groups using free and paid versions of chatbots used in education can be examined.

The findings showed that the chatbot usage intentions of university students in computer programming education differed according to the experience of using chatbots in education. According to the finding, the intentions and acceptance of university students who have previous experience of using chatbots in education are higher than those who do not use chatbots. This is the expected result in the study. Because technology usage intention and acceptance are among the primary conditions of use (Teo et al., 2019).

The study indicated that the chatbot usage intentions of university students in computer programming education did not differ according to the device used in chatbots education. Since smartphones are widely used among university students, it was expected that there would be a difference in favour of smartphones in terms of chatbots use in programming education. However, it is thought that computers, which have a larger screen than smartphones in terms of long lines of programming language codes and detection of errors, will also play a role in the intention to use chatbots in education. For this reason, the need to repeat future studies on this variable in terms of chatbots usage intention has emerged. It is also thought that the intention and acceptance levels of university students to use chatbots in education will increase, especially with the introduction of chatbots as mobile applications on smartphones.

It was determined that university students' intentions to use chatbots in computer programming education differ according to the frequency of chatbots use in education. It has been determined that university students who use chatbots in education 21-30 times a week have significantly higher chatbots usage intentions than those who use 1-10 times and 11-20 times. The finding revealed an expected result. Because high intention contributes to the use of technology and the increase in this use. Finally, it is thought that the intention to use and duration of use of educational chatbots will increase over time, as chatbots are integrated into teaching environments and teaching approaches in the most appropriate way, courses that will optimize interaction with chatbots, which are artificial intelligence language models, are added to the curriculum and chatbots develop day by day.

The analysis revealed that the chatbots usage intentions of university students in computer programming education did not differ according to the roles attributed to chatbots in programming education. As a result of the finding, it is thought that the use of chatbots for mentoring, assisting, and learning purposes in programming education is of similar importance for university students. In a supportive study, chatbots were used by more than 700 students for one year in terms of mentoring and promising results emerged in terms of the usability of digital mentoring support for students (Neumann et al., 2021). Singh (2018) and Clark (2018), Intelligent tutoring systems for learning, teaching assistant and mentoring processes are within the scope of the roles that chatbots, which are artificial intelligence language models, can play in teaching/learning processes. For this reason, when it is considered that chatbots can undertake all three roles in programming education in the study, the fact that there is no difference shows that students intend to use chatbots in terms of all roles. In addition, it is thought that chatbots can enter all educational roles with the effect of easier for use, user friendly (Colace et al., 2018) and humane artificial intelligence than previous technology-supported applications and learning approaches in terms of providing learning at their own pace and supporting the learning experience outside of school. However, studies in the related field are needed to support this.

In conclusion, it is thought that the intention of university students to accept the use of chatbots in computer programming education is at a good level and this intention will increase day by day. Because, as it was determined in the study, the chatbots that university students intensively prefer in education is the ChatGPT application, which is widely used nowadays. With the development and popularisation of chatbots to be used in other educational fields, the integration of chatbots into educational environments and curricula will be even faster. ChatGPT, which already has a robust language model, is attracting great interest as a possible way to improve the educational experience of university students (Huallpa, 2023). Although not very long, in the coming years, Prompt engineering courses, which involve using specific inputs or "prompts" to influence chatbots such as ChatGPT, will be added to the curricula, enabling students to effectively create and use prompts and increase their interaction with artificial intelligence. In this way, the use of artificial intelligence in education will become widespread among university students whose interaction with artificial intelligence increases. In addition, it is thought that the effect of chatbots such as "copilot", the artificial intelligence language model of Microsoft company, and "codex" produced by Open AI company on the computer programming education as the main subject of the study will increase day by day. However, in future studies, it is suggested that studies should be conducted to understand the effects of using these tools in computer programming education (Philbin, 2023) and to reveal the factors affecting students' chatbots intentions (Ragneb et al., 2022), especially including students' concerns about the misuse of chatbots in education. Finally, it is important to provide appropriate training to instructors through in-service training to teach them how to use artificial intelligence applications as a teaching method that meets the needs of each student (Ragneb et al., 2022).

References

- Aktay, S., Gök, S., & Uzunoğlu, D. (2023). ChatGPT in Education. *Türk Akademik Yayınlar Dergisi (TAY Journal)*, 7(2), 378-406. Retrieved from <https://dergipark.org.tr/en/pub/tayjournal/issue/76658/1259832>
- Biswas, S. (2023). Role of ChatGPT in Computer Programming.: ChatGPT in Computer Programming. *Mesopotamian Journal of Computer Science*, 2023, 9-15. <https://doi.org/10.58496/MJCSC/2023/002>
- Buyukozturk, Ş., Kılıc-Cakmak, E., Akgun, O., Karadeniz, S., & Demirel, F. (2008). *Eğitimde Bilimsel Araştırma Yöntemleri [Scientific Research Methods in Education]*, (1th ed), Pegem Akademi: Ankara.
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20(1), 43. <https://doi.org/10.1186/s41239-023-00411-8>
- Clark, D. (2018, December 17). *10 uses for Chatbots in learning (with examples)* [Blog post]. Retrieved from <http://donaldclarkplanb.blogspot.com/2017/12/10-uses-for-chatbots-in-learning-with.html>
- Colace, F., De Santo, M., Lombardi, M., Pascale, F., Pietrosanto, A., & Lemma, S. (2018). Chatbot for e-learning: A case of study. *International Journal of Mechanical Engineering and Robotics Research*, 7(5), 528-533. Retrieved from <https://www.ijmerr.com/uploadfile/2018/0831/20180831043721869.pdf>
- Draxler, F., Buschek, D., Tavast, M., Hämäläinen, P., Schmidt, A., Kulshrestha, J., & Welsch, R. (2023). Gender, Age, and Technology Education Influence the Adoption and Appropriation of LLMs. In *Manuscript submitted to ACM. ACM, New York, NY, USA*, 15 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>
- Dwivedi, Y. K., Rana, N. P., Chen, H., & Williams, M. D. (2011). A Meta-analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT). In *Governance and Sustainability in Information Systems. Managing the Transfer and Diffusion of IT: IFIP WG 8.6 International Working Conference*, Hamburg, Germany, September 22-24, 2011. Proceedings (pp. 155-170). Springer Berlin Heidelberg.
- Fryer, L. K., Thompson, A., Nakao, K., Howarth, M., & Gallacher, A. (2020). Supporting self-efficacy beliefs and interest as educational inputs and outcomes: Framing AI and Human partnered task experiences. *Learning and Individual Differences*, 80, 101850. <https://doi.org/10.1016/j.lindif.2020.101850>
- Gill, S. S., & Kaur, R. (2023). ChatGPT: Vision and challenges. *Internet of Things and Cyber-Physical Systems*, 3, 262-271. <https://doi.org/10.1016/j.iotcps.2023.05.004>
- Holmes, W., Bialik, M., & Fadel, C. (2023). *Artificial intelligence in education*. Globethics Publications.
- Huallpa, J. J. (2023). Exploring the ethical considerations of using Chat GPT in university education. *Periodicals of Engineering and Natural Sciences*, 11(4), 105-115. <http://dx.doi.org/10.21533/pen.v11i4.3770>
- Iqbal, S. M., Mathew, R., Tawafak, R. M., & Alfarsi, G. (2021, July). A web-based model to enhance algorithmic thinking for novice programmers. *E-Learning and Digital Media*, 18(6), 616-633. <https://doi.org/10.1177/20427530211026988>

- Keles (2023, November). *Chat GPT Nedir? Chat GPT Nasıl Kullanılır? [What is Chat GPT? How to Use Chat GPT?]* Retrieved from: <https://www.ticimax.com/blog/chat-gpt-nedir>
- Kerlyl, A., Hall, P., & Bull, S. (2006, December). Bringing chatbots into education: Towards natural language negotiation of open learner models. In *International conference on innovative techniques and applications of artificial intelligence* (pp. 179-192). London: Springer London.
- Kim, J. W., Jo, H. I., & Lee, B. G. (2019). The study on the factors influencing on the behavioral intention of chatbots service for the financial sector: Focusing on the UTAUT model. *Journal of Digital Contents Society*, 20(1), 41-50. <http://dx.doi.org/10.9728/dcs.2019.20.1.41>
- Luo, B., Lau, R. Y., Li, C., & Si, Y. W. (2022). A critical review of state-of-the-art chatbots designs and applications. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 12(1), e1434. <https://doi.org/10.1002/widm.1434>
- Malik, S. I., Ashfque, M. W., Tawafak, R. M., Al-Farsi, G., Usmani, N. A., & Khudayer, B. H. (2022). A Chatbot to Facilitate Student Learning in a Programming 1 Course: A Gendered Analysis. *International Journal of Virtual and Personal Learning Environments (IJVPLE)*, 12(1), 1-20. <https://doi.org/10.4018/IJVPLE.310007>
- McCracken, M., Almstrum, V., Diaz, D., Guzdial, M., Hagan, D., Kolikant, Y. B. D., ... & Wilusz, T. (2001). A multi-national, multi-institutional study of assessment of programming skills of first-year CS students. *Working group reports from ITiCSE on Innovation and technology in computer science education* (pp. 125-180).
- Mokmin, N. A. M., & Ibrahim, N. A. (2021). The evaluation of chatbots as a tool for health literacy education among undergraduate students. *Education and Information Technologies*, 26(5), 6033-6049. <https://doi.org/10.1007/s10639-021-10542-y>
- Moon, J., Yang, R., Cha, S., & Kim, S. B. (2023, August). ChatGPT vs Mentor: Programming Language Learning Assistance System for Beginners. In *2023 IEEE 8th International Conference on Software Engineering and Computer Systems (ICSECS)* (pp. 106-110). IEEE.
- Neumann, A. T., Arndt, T., Köbis, L., Meissner, R., Martin, A., de Lange, P., ... & Wollersheim, H. W. (2021). Chatbots as a tool to scale mentoring processes: Individually supporting self-study in higher education. *Frontiers in artificial intelligence*, 4, 668220. <https://doi.org/10.3389/frai.2021.668220>
- Okonkwo, C. W., & Ade-Ibijola, A. (2020). Python-Bot: A chatbots for teaching python programming. *Engineering Letters*, 29(1), 25-34. Retrieved from https://www.engineeringletters.com/issues_v29/issue_1/EL_29_1_03.pdf
- Qian, Y., & Lehman, J. (2017). Students' misconceptions and other difficulties in introductory programming: A literature review. *ACM Transactions on Computing Education (TOCE)*, 18(1), 1-24. <https://doi.org/10.1145/3077618>
- Philbin, C. A. (2023). Exploring the Potential of Artificial Intelligence Program Generators in Computer Programming Education for Students. *ACM Inroads*, 14(3), 30-38. <https://doi.org/10.1145/3610406>
- Raffaghelli, J. E., Rodríguez, M. E., Guerrero-Roldán, A. E., & Baneres, D. (2022). Applying the UTAUT model to explain the students' acceptance of an early warning system in Higher Education. *Computers & Education*, 182, 104468. <https://doi.org/10.1016/j.compedu.2022.104468>

- Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A. (2022). Investigating the acceptance of applying chatbot (Artificial intelligence) technology among higher education students in Egypt. *International Journal of Higher Education Management*, 8(2), 1-13. Retrieved from <https://d1wqtxts1xzle7.cloudfront.net/96162300/2022-02-28-20-55-56-PM-libre.pdf>
- Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. *Applied Sciences*, 13(9), 5783. <https://doi.org/10.3390/app13095783>
- Singh, R. (2018, May 2). *AI and Chatbots in Education: What Does The Future Hold?* [Blog post] Retrieved from <https://chatbotssmagazine.com/ai-and-chatbots-in-education-what-does-the-futurehold-9772f5c13960>
- Surameery, N. M. S., & Shakor, M. Y. (2023). Use chat gpt to solve programming bugs. *International Journal of Information Technology & Computer Engineering (IJITC)*, 3(01), 17-22. <https://doi.org/10.55529/ijitc.31.17.22>
- Şişman, B., & Küçük, S. (2018). Öğretmen adaylarının robotik programlamada akış, kaygı ve bilişsel yük seviyeleri [Pre-service teachers' flow, anxiety and cognitive load levels in robotic programming]. *Eğitim teknolojisi kuram ve uygulama*, 8(2), 125-156. <https://doi.org/10.17943/etku.366193>
- Teo, T., Doleck, T., Bazalais, P., & Lemay, D. J. (2019). Exploring the drivers of technology acceptance: a study of Nepali school students. *Educational Technology Research and Development*, 67, 495-517. <https://doi.org/10.1007/s11423-019-09654-7>
- Topal, A. D., Eren, C. D., & Geçer, A. K. (2021). Chatbot application in a 5th grade science course. *Education and Information Technologies*, 26, 6241-6265. <https://doi.org/10.1007/s10639-021-10627-8>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
- Verleger, M., & Pembridge, J. (2018, October). A pilot study integrating an AI-driven chatbots in an introductory programming course. In *2018 IEEE frontiers in education conference (FIE)* (pp. 1-4). IEEE.
- West M., Kraut, R., & Han, Ei. C. (2019). *I'd blush if I could: closing gender divides in digital skills through education. Technical Report. UNESCO.* Retrieved from <https://repositorio.minedu.gob.pe/bitstream/handle/20.500.12799/6598/I%27d%20blush%20if%20I%20could%20closing%20gender%20divides%20in%20digital%20skills%20throug%20education.pdf>
- Vukojičić, M., & Krstić, J. (2023). ChatGPT in programming education: ChatGPT as a programming assistant. *InspirED Teachers' Voice*, 2023(1), 7-13. Retrieved from <https://www.teachers-voice.org/index.php/inspired/article/view/10/2>
- Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of enterprise information management*, 28(3), 443-488. <https://doi.org/10.1108/JEIM-09-2014-0088>
- Yildiz-Durak, H. (2023). Conversational agent-based guidance: examining the effect of frequency and satisfaction on visual design self-efficacy, engagement, satisfaction, and learner autonomy. *Education and Information Technologies*, 28(1), 471-488. <https://doi.org/10.1007/s10639-022-11149-7>

Yildiz-Durak, H., & Onan, A. (2023). Adaptation of Behavioral Intention to Use and Learn Chatbot in Education Scale into Turkish. *Journal of Ahmet Keleşoğlu Education Faculty*, 5(3), 1162-1172. <https://doi.org/10.38151/akef.2023.104>

Yilmaz, R., & Yilmaz, F. G. K. (2023). Augmented intelligence in programming learning: Examining student views on the use of ChatGPT for programming learning. *Computers in Human Behavior: Artificial Humans*, 1(2), 100005. <https://doi.org/10.1016/j.chbah.2023.100005>

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Past, Present, and Future of Artificial Intelligence in Education: A Bibliometric Study

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Abstract: With the rapid advancement in technology, artificial intelligence has permeated every aspect of daily life. Education is no exception. Artificial intelligence in education (AIED) has attracted great interest in the academic field. This bibliometric study aims to analyze and document the literature on AIED from its emergence to 2023. AIED-related publications were analysed for patterns, trends, and potential research gaps in the field. The search parameters were 'Artificial Intelligence in Education' in the article title, abstract, or topic. In order to examine the evolution of the concept holistically, no date restrictions were applied. The search, therefore, covered studies published from 1989 to 2023, with the first publication indexed in the Web of Science database marking the beginning of the timeline. The Web of Science was used as the main database and 905 studies were screened during the search. The Biblioshiny of R Software was used for descriptive and network analysis. The annual growth rate was calculated as 18.7%, indicating significant interest in the field. The results also showed that China, the USA, the UK, Australia, and Spain are the leading countries in the field of AIED. Through thematic analysis, trending topics and engine, core, emerging, and niche themes were uncovered. Based on the research findings, the current study takes a forward-looking stance and goes beyond merely summarizing the past and present to provide insights on future linkages.

Keywords: Artificial Intelligence, Aied, Bibliometric, Education

1. Introduction

Technology has advanced significantly in recent years. These advancements have impacted the education field, similar to many other fields. Owing to these advancements in technology, artificial intelligence (AI) has ushered in a new era in education and is seen as a driving force of technology (Arslan, 2020). First coined in the second half of the 20th century by McCarthy (Cope et al., 2021), artificial intelligence refers to 'the science of endowing programs with the ability to change themselves for the better as a result of their own experiences' (Schank, 1987, p. 64). AI is a promising technology designed to develop computer systems that perform intelligent and adaptive behaviors, reflecting the ability to learn from their environment. Hence, AI can be described as a system that mimics the human brain to complete specified tasks and can recursively improve through experience gained from that task (İşler & Kılıç, 2021).

The field of application of AI is prevalent from medicine to tourism. While AI has found innovative applications across several industries, its incorporation into the education industry is still in the early phase (Alam, 2021). Despite several attempts at basic commercial usage, the application of AI technologies in the educational field has not yet reached its potential. Within the educational landscape, AI is not a standalone entity but rather seamlessly embedded within broader technological trends. The primary focus of developmental research revolves around developing AI technologies rather than exploring their real-world applications. This focus has led to a slower progression of AI into new fields such as education.

Despite its slow progress in the educational field, the benefits of AI cannot be overlooked. AI has already been integrated into several aspects of the teaching-learning process, from adaptive assessments to automated assessment constructions (Swiecki et al., 2022). For example, automated grading is among the several benefits of AI. AI-supported automated grading systems can replicate a teacher's actions in terms of assessing and evaluating a student's assignment. Offering personalised learning paths is

another benefit of AI. Many AI applications in the educational field customise learning by providing learners with individualised learning plans and instructions; analysing learners' needs, strengths, and interests; and subsequently tailoring the teaching-learning process. Another benefit of AI lies in its ability to facilitate adaptive learning approaches (Owoc et al., 2019). In contrast to conventional classroom education, which is mostly one-size-fits-all, AI-based adaptive learning systems are crafted to optimise the teaching-learning process. One way that these systems use to maximise learning efficacy is to gather and analyse students' behavioural data and provide timely personalised feedback accordingly (Cui et al., 2018), which, in turn, enhances learners' educational experiences.

As AI offers numerous advantages, it has garnered substantial scholarly attention. As a result of researchers' active promotion and investigation of the concept, considerable scholarly output has been produced about AIED. While scholarly output is crucial in several aspects, such as establishing a foundation for future research and enabling knowledge dissemination, synthesising and interpreting this increasing volume of scientific research are essential. Hence, several review studies on AIED have been conducted (Crompton & Burke, 2023; Xu & Ouyang, 2022; Zawacki-Richter et al., 2019). Some of those review studies adopted a systematic review strategy. For example, Xu and Ouyang (2022) executed a systematic review study to identify, classify, and summarise the studies portraying the wide-ranging roles of AIED. Several databases, such as Scopus, Science Direct, and Web of Science, were scanned. However, they limited the time period between 2005 and the first eight months of 2021. Narrowing down their focus on the context of the teaching-learning process, Xu and Ouyang (2022) systematically analysed 164 publications and reported only 51 of them due to space restrictions. As a result of their systematic review, Xu and Ouyang (2022) proposed a conceptual framework based on AI's roles in instructional and learning processes. In the framework, three roles of AI were proposed: "AI as a new subject", "AI as a direct mediator", and "AI as a supplementary assistant" (Xu & Ouyang, 2022, p. 4213). According to the framework, in the first category, AI substitutes for the original subjects; in the second category, AI serves as a direct mediator to link subjects; and in the last category, AI has the role of a supplementary assistant and indirectly supports subjects. In another study, Crompton and Burke (2023) systematically reviewed publications on AI in higher education between 2016 and 2022. A wide range of databases, including EBSCO, JSTOR, and Web of Science, Crompton and Burke (2023) scanned to review 138 studies. While the previously conducted systematic reviews suggested that most of the studies were published in the USA, this trend has recently changed, and China overtook the USA in terms of the number of publications. Another significant finding of Crompton and Burke's (2023) review lies in its categorisation of the themes based on the usage of AI in higher education. Hence, they reached five categories: '(1) Assessment/Evaluation, (2) Predicting, (3) AI Assistant, (4) Intelligent Tutoring System (ITS), and (5) Managing Student Learning' (Crompton & Burke, 2023, p. 19-20).

In addition to systematic reviews, bibliometric studies have been conducted within the field of AIED (Chen et al., 2022; Guan et al., 2022; Prahani et al., 2022). These bibliometric studies are highly important as they provide quantitative insights into publication trends, citation patterns, and scholarly impact within the field of AIED. For instance, in his bibliometric study, Talan (2021) explored the distributions of publications based on country and year; provided a citation pattern analysis of institutions, authors, journals, and documents; and mapped co-authors, co-citations, and co-occurrence analyses on the AIED website. Examining the publications on AIED within the past two decades (2001-2021), Talan (2021) used the Web of Science as the database and several keywords related to the term AIED such as "artificial intelligence" OR "machine intelligence" OR "neural network*" OR "machine learn*" OR "deep learn*" OR "natural language process*" OR "thinking computer system" OR "expert system" OR "evolutionary computation". Hence, Talan (2021) identified a total of 2,686 publications on the topic. His results were in line with the previous literature in terms of the distribution of the publications by country, a steady increase in the number of publications each year, the distribution of top journals on AIED, and the leading authors. However, his analysis revealed that institutions located

in Taiwan and Australia, in addition to the previously identified influential institutions in the USA and UK have emerged as influential in AIEd.

A more recent bibliometric study, conducted by Metli (2023), screened 6498 studies published between 1984 and 2022 in the Web of Science and indexed them in "SCI_EXPANDED, SSCI, ESCI". Like in Talan's study (2021), Metli (2023, p. 285) also extended his search keywords to "Artificial Intelligence" OR "Deep Learning" OR "Machine Learning" OR "Natural Language Processing". In contrast to Talan (2021), Metli (2023) revealed that China and India were among the top five leading countries in terms of producing the most publications, alongside the USA, the UK, and Australia. Another noteworthy finding of Metli (2023) was the evolution of keyword popularity. The analysis documented the shift of certain concepts over time. It was revealed that while e-learning and higher education were popular terms in 2020, artificial intelligence, machine learning, and deep learning gained popularity in 2021.

Apart from the abovementioned studies, various other scientific studies were also conducted on AIEd. Some employed narrative overview methods to predict the potential impact of artificial technologies on the teaching-learning process and anticipate potential changes in the educational field (Chassignol et al., 2018). Others have focused only on AI in higher education (Bearman, 2023; Hinojo-Lucena et al., 2019; Maphosa & Maphosa, 2023; Zawacki-Richter et al., 2019). However, other scholars have investigated the AIEd concept, narrowing their focus down to a specific country or region, such as in China (Knox, 2020) or Turkey (İçen, 2020). Recognising that all these studies have significantly contributed to the literature and that the article growth rate increases by 22.68% each year (Metli, 2023), it is of great importance to conduct an up-to-date and holistic bibliometric study that complements previous studies. A new bibliometric study is indispensable for understanding the dynamics of the field and updating the accumulation of knowledge. This study, which is conducted both to determine the current state of the field and to verify or compare previous findings, plays a critical role in the continuity of scientific progress. Hence, the current study aims to holistically investigate the current trends, patterns, and future directions of AIEd. The purpose of this research is to offer insights to field experts to discover diverse research subjects and mitigate redundancies among studies. In line with these aims, the research questions of the current study address the following:

1. What is the overview of the publications in the AIEd field?
2. What are the leading authors, countries, and publication outlets in the AIEd field?
3. How do collaborations among the relevant authors and countries manifest in the AIEd field?
4. What are the trends and patterns in the AIEd field?

2. Methods

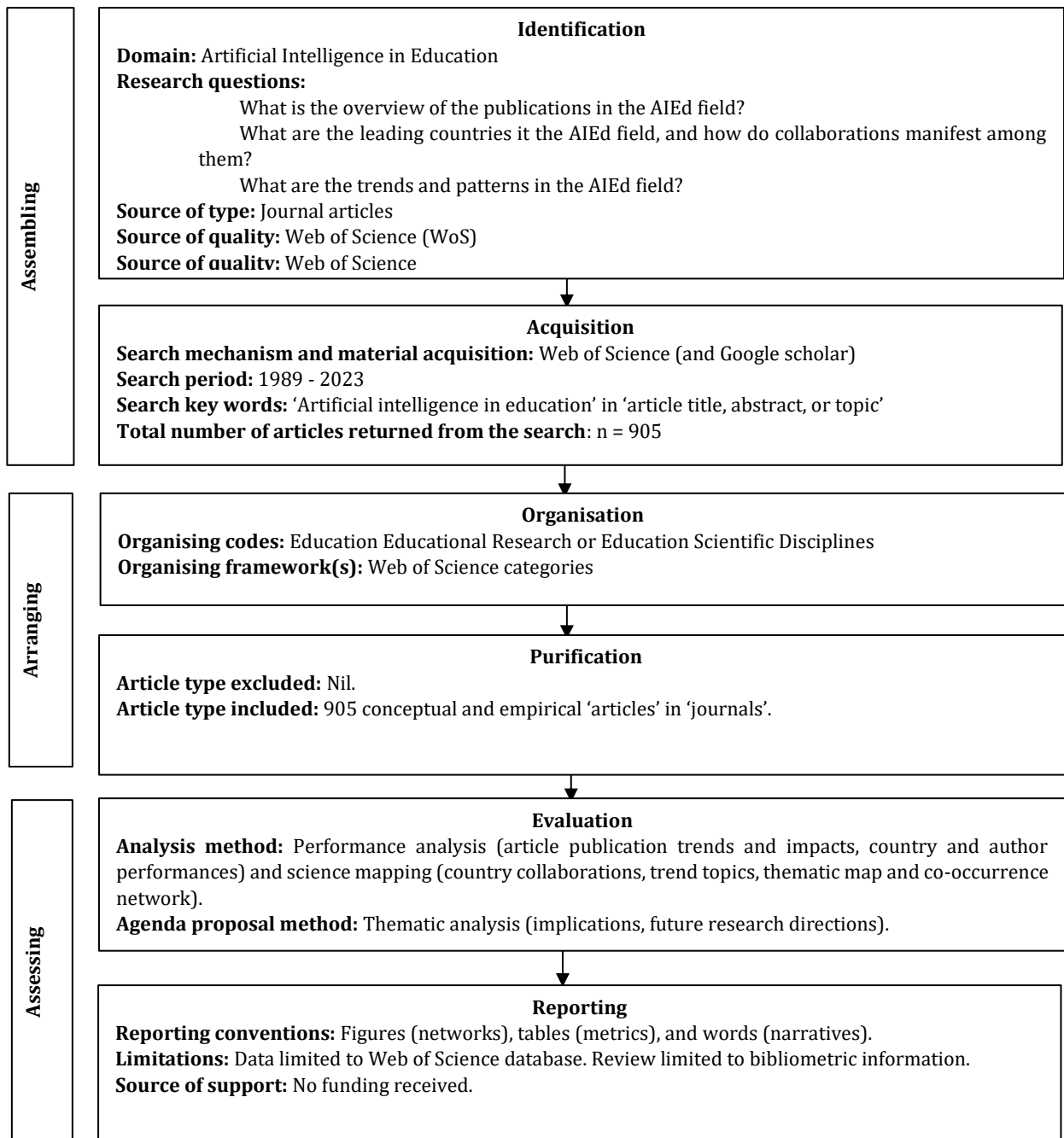
The current study adapts the scientific mapping analysis method. The methodology for the current study involves two main phases: the selection of document sources and the conduct of bibliometric analysis. The following sections explain these stages.

2.1. Selection of document sources

The Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) protocol was followed to maintain clarity and transparency (Paul et al., 2021). Figure 1 below describes the work flow for the current study.

Figure 1

SPAR-4-SLR protocol



As can be seen in Figure 1, the Web of Science (WoS) was selected for the data query because it is a sophisticated research repository and offers extensive bibliographic data, including authors, their affiliations, and cited works. The search query for the current study included 'Artificial Intelligence in Education'. All the documents that incorporated the search query within their abstracts, titles, or topics were included. As the current study aimed to trace the past, present, and future of AI within the educational field, the filters were applied to include the documents that were only listed under the categories of Education Educational Research or Education Scientific Disciplines. To obtain a holistic view, all document types, including book chapters and proceedings papers, as well as articles and early access were screened. All WoS indices were also included. The time limit was not applied to observe the progress of the term since its emergence. This means that publications between 1989, the date of the

first publication indexed in WoS, and 2023, the date of the last analyses of this study, were examined. Consequently, 905 documents were screened.

2.2. Bibliometric analysis

With the aim of conducting a quantitative evaluation of the documents, bibliometric methods were employed. Bibliometric studies, also referred to as scientific mapping, are useful methods for visually mapping the body of scientific literature in relation to a specific research area (Huang, Yang, Wang, Wu, Su & Liang, 2019; Song, Chen, Hao, Liu & Lan, 2019). Bibliometric studies involve evaluating a particular term by analysing and evaluating the impact of the relevant researchers and tracking the evolving patterns or changes in that specific concept over time (Hallinger & Kovačević, 2019). Bibliometric studies offer a comprehensive understanding of the field by categorising research according to publications, authors, and journals (Merigó & Yang, 2017; Sreenivasan & Suresh, 2023). Studies employing bibliometric methods provide insights into citation impact, establishing a correlation between author productivity, the influence of the scientific community, and publication success (Yu & Shi, 2015). For this study, Bibliometrix Software in the RStudio statistical analysis program was used. To visually present the data, the Biblioshiny Software package was used. The Biblioshiny package allowed several statistical analyses, such as conceptual and intellectual structure analyses, to be performed.

3. Results

3.1. Overview of the publications in the AIEd field

3.1.1. Overview of the main information

The aim of the study was to investigate the historical progression, current status, and anticipated future developments within the field of AIEd studies. With this in mind, 905 records published between 1989 and 2023 in 271 journals with contributions from 2,484 authors were screened, as shown in Figure 2 below.

Figure 2

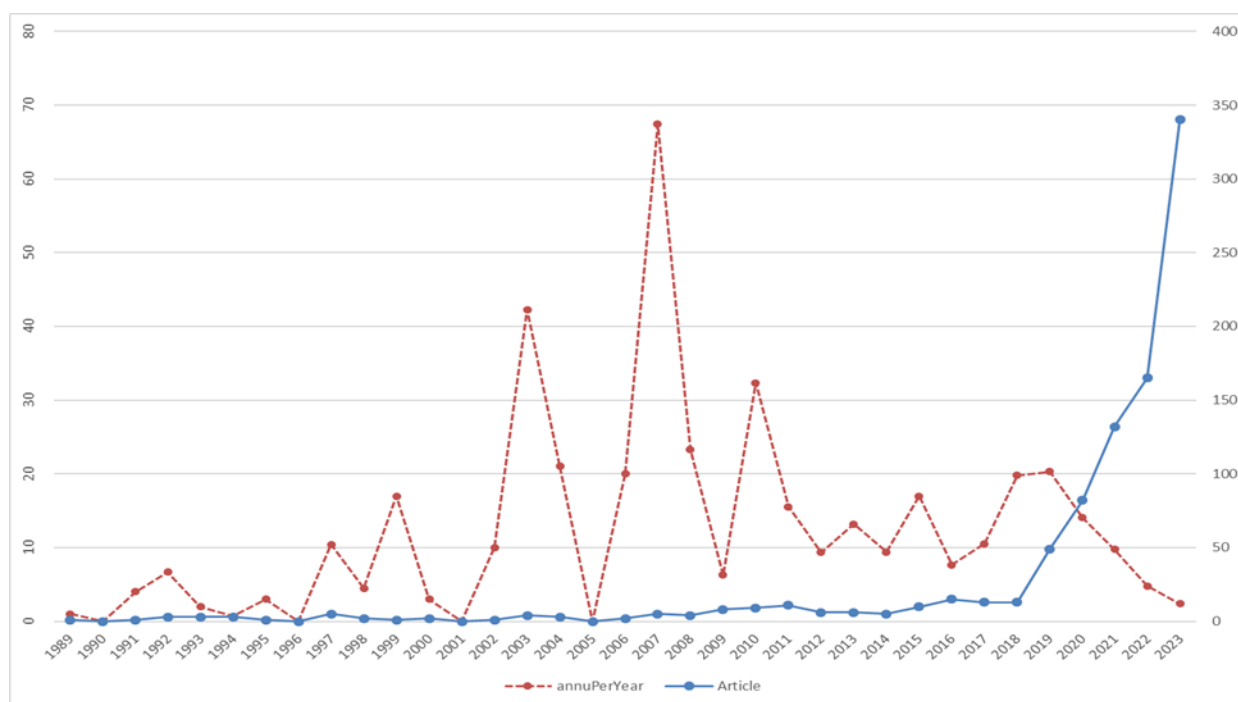
Overview of the Main Information



The analysis yielded 2,484 authors and 175 published single-authored documents. The review encompassed 36,537 references and approximately 8 citations per document. The yearly growth rate was calculated as 18.7%.

3.1.2. Distribution of annual publications and average citations per year

Biblioshiny analysed data regarding yearly scientific output and average citation counts. A graphical representation was employed to encapsulate the corpus of works and associated citations within a given year below.

Figure 3*Annual Scientific Production and Average Citations per Year*

As can be inferred from Figure 3, an analysis of the yearly production of documents on AIEd revealed that the concept gained momentum after 2019. The number of studies published before 2018 was calculated as 137. While there were only a few publications for almost three decades since the emergence of the concept, 637 publications were produced during the last three years. The figure above demonstrates that no publications produced in 1990, 1996, or 2001 included AIEd in their abstracts, titles, or topics. It can also be seen that only a single document was detected for the years 1989, 1991, 1995, 1999, and 2002. Three documents were produced annually in the years 1992, 1993, 1994, and 2004. Figure 3 suggests that there has been a sudden increase in interest and, subsequently, the number of publications in recent years. A total of 132, 165, and 340 documents were produced in 2021, 2022, and 2023, respectively.

For the yearly average citations, 2019 and 2007 had the highest average citations per year, 4.1 and 4, respectively. Additionally, fluctuations can be observed between those years. A sudden decrease was observed in 2008, with an average of 1.4 citations per year. Although the average citations per year increased to 2.3 in 2010, this number decreased to 1.2 in 2011 and 0.8 in 2012. A steady decrease was also observed after 2019.

3.2. Leading authors, countries, and publication outlets in the AIEd field

3.2.1. Authors and their contributions

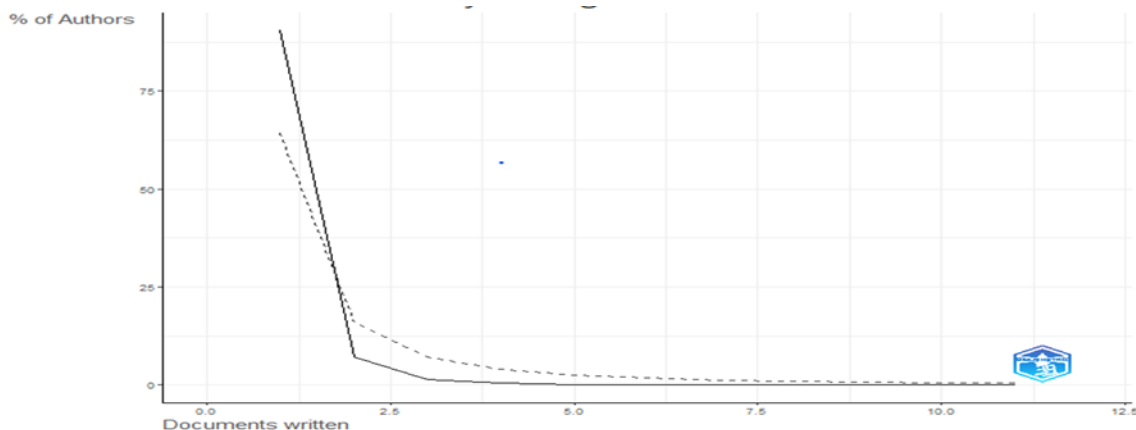
Examining publications through the lens of authorship reveals insights about notable contributors to the field of AIEd. These authors are classified by their productivity, quantified by the number of papers they have published in their field. Table 1 presents the five authors who contributed the most to the field.

Table 1*The Five Most Relevant Authors and Number of Publications*

Authors	Publications
CHIU TKF	11
HWANG GJ	10
CHAI CS	9
WANG Y	8
XIE H	8

As can be seen in Table 1, Chiu TKF (n=11), Hwang GJ (n=10), Chai CS (n=9), Wang Y (n=8), and Xie H (n=8) were the authors who contributed the most to the field.

Author productivity was also analysed based on Lotka's Law (Lotka, 1926) distribution. Lotka's Law demonstrates the frequency distribution of scientific productivity among authors. This law suggests that the number of authors with a specified number of publications follows an inverse square distribution. Essentially, it states that a small number of authors publish the majority of publications, and a large number of authors publish fewer publications. Authors who have published more than five documents can be considered experts in the field and core authors (Metli, 2023). Figure 4 illustrates the relevance of the authors in the AIED field.

Figure 4*Author Productivity by Lotka's Law*

As Figure 4 suggests, author relevance in the AIED field mostly aligns with the actual Lotka curve. The analysis showed that 2,246 authors published only one document. This number consists of nearly 90% of the authors. The results also showed that while 176 authors contributed to the field in association with only two articles, 33 authors published three documents. The percentage of authors who contributed to the field with five or more publications appeared to be only 0.64.

3.2.2. Most cited documents

The most cited document has the potential to represent the core body of knowledge in a relevant field and can, therefore, be considered an indispensable primary source for understanding or contextualizing the field. Hence, examining the most cited documents is important for comprehending the production and diffusion of knowledge within the discipline. With this in mind, the top ten most cited documents in this field are presented in Figure 5.

Figure 5

Most cited documents

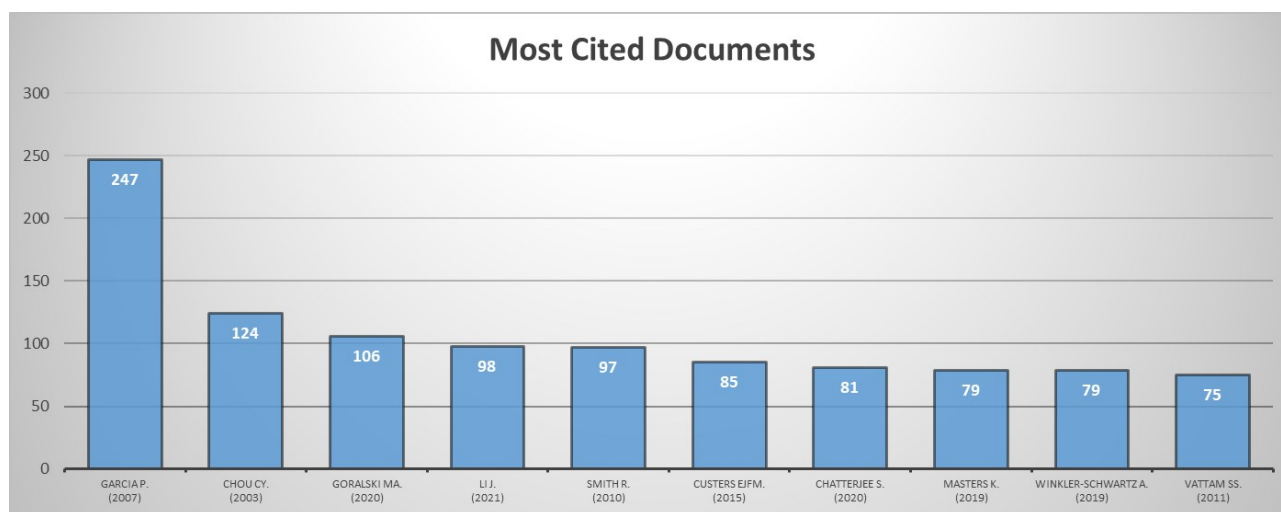


Figure 5 demonstrates that Garcia P. (2007) is the study with the highest number of citations in this field, with a total of 247 citations, followed by Chuo CY (2003) with 124 citations and Goralski MA (2020) with 106 citations. In addition, it was noted that Li J. (2021) and Smith R. (2010) were very close to each other in the top five with 98 and 94 citations, respectively.

3.2.3. Leading countries in the field

Within Bibliometrix's analysis of country-specific production, a distinct pattern emerges, delineating the five countries that exhibit the highest frequency in generating documents within the AIEd research field. Figure 6 visually illustrates the trajectory of each country's output.

Figure 6

Country Scientific Production

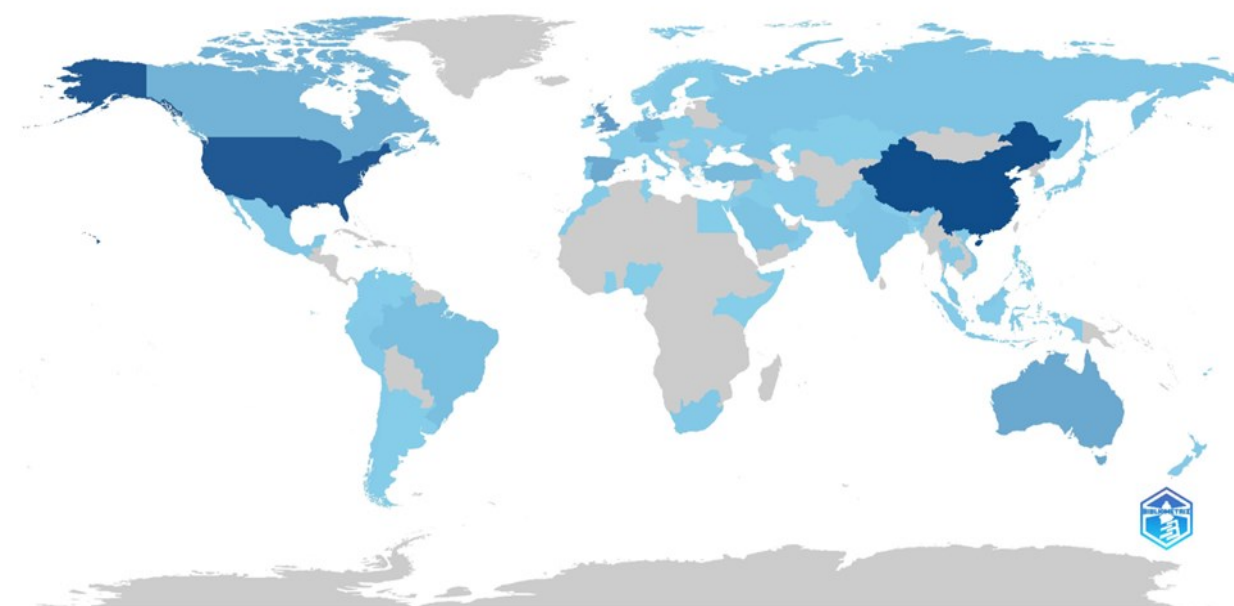


Figure 6 demonstrates the top five leading countries in the field of AIEd based on their production. In the figure, as the shade of blue increases, there is a positive correlation with the country's productivity. Based on the data obtained from Bibliometrix, China (n=624), the USA (n=565), the UK (n=226),

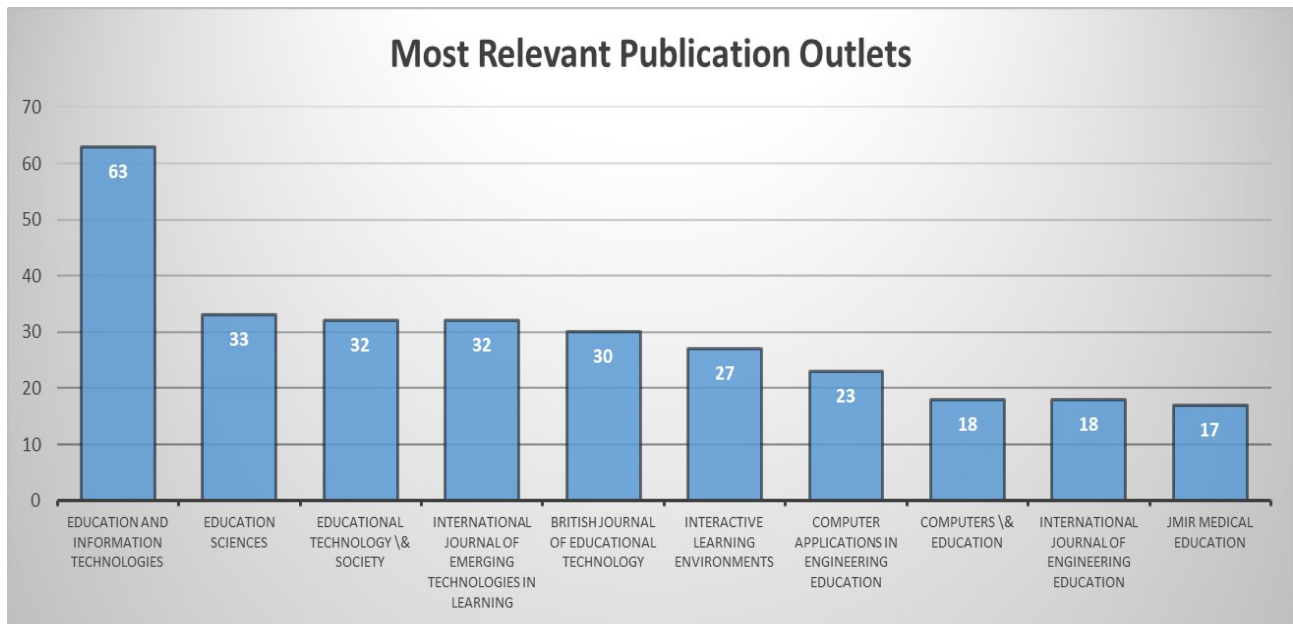
Australia (n=169), and Spain (n=164) are among the top five countries. The collaboration maps of these countries are visualised below. Increasing shades of red indicate increasing levels of cooperation between the entities represented. This darker shade suggests the frequency and strength of collaboration observed in the dataset.

3.2.4. Most relevant publication outlets

Identifying the best journals in a field is valuable as it provides a specific resource for those interested in that field. Hence, the most relevant publication outlets are presented below.

Figure 7

Most Relevant Publication Outlets



Upon the analysis of Figure 7, it can be seen that the Journal of Education and Information Technologies (n=63) is the main source of coverage in this area. This is followed by Educational Sciences (n=33), Educational Technology & Society (n=32), International Journal of Emerging Technologies in Learning (n=32), and British Journal of Educational Technology (n=30) with almost half the number of publications.

3.3. Collaborative links among the authors and countries

Identifying the most collaborating authors and countries in a field is crucial for researchers. This data is used to identify countries and institutions operating in similar fields. This helps researchers identify opportunities for collaboration and shape their career goals. At the same time, knowing the global development of a field and its leading authors and countries allows researchers to follow trends in their field and identify potential partners for international cooperation. As a result, analysis based on this data enables researchers to be effective and efficient in the international arena. Therefore, the data of the most collaborating authors and countries in the field are presented below.

Figure 8

Collaboration Among the Authors in the Field

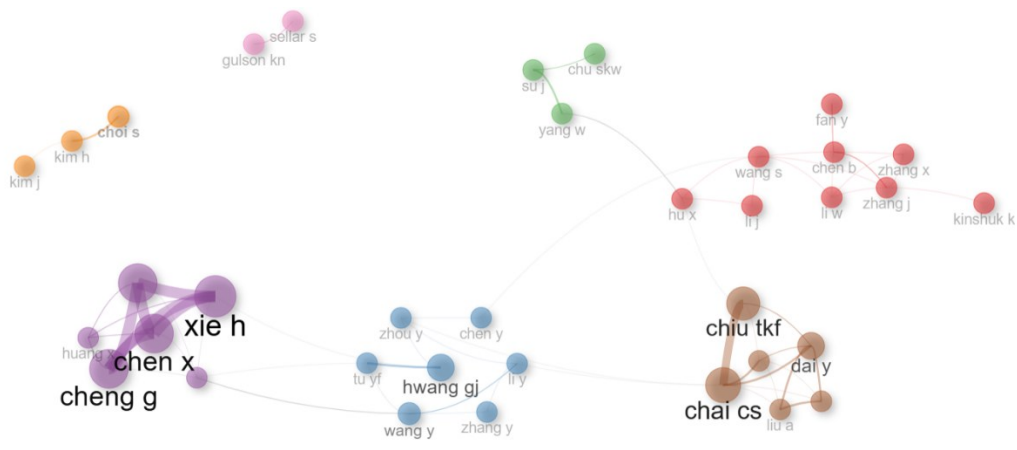
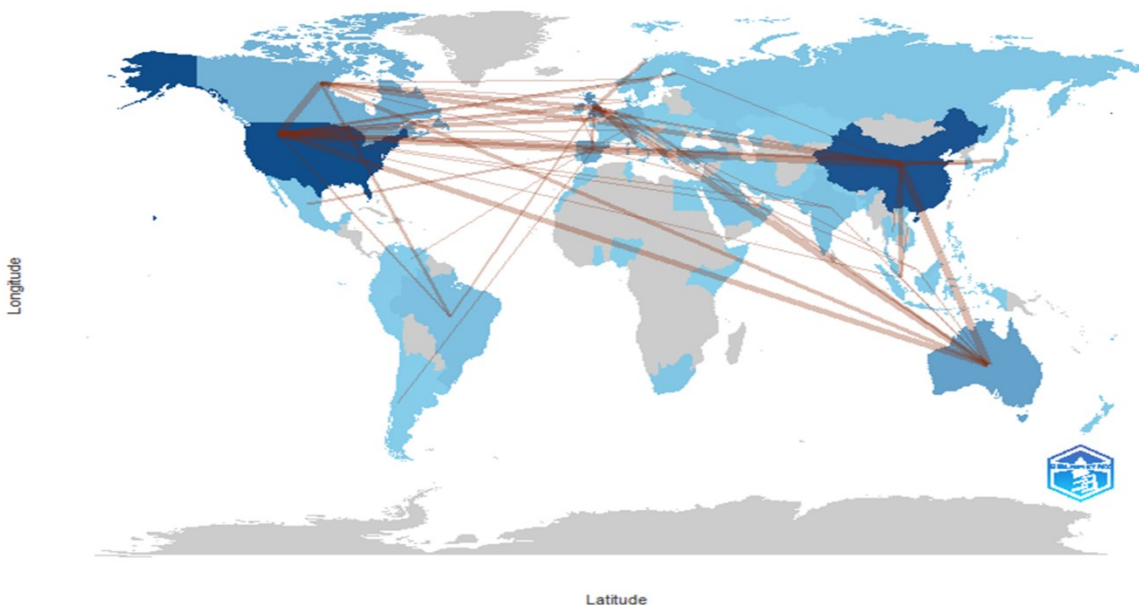


Figure 8 demonstrates that authors collaborating in this field are grouped into seven clusters. Although collaborations are predominantly within clusters, some authors also collaborate across clusters. For example, there are links between Yang W and Hu X, Hu X and Chiu TKF, and Chai CS and Li Y in different clusters. In particular, the presence of collaboration links between specific authors across different cluster groups suggests that these authors are active in a broad network and could potentially converge on different research areas or projects. This suggests that the field values collaboration and knowledge sharing and that such collaboration can enhance research results and knowledge production. When the collaborations among countries were analysed, the results of the network analysis presented in the figure below were obtained. The network structure shown in the figure visually represents the cooperation links between various countries and the intensity of these links.

Figure 9

Collaboration World Map



Upon the analysis of Figure 9, it appeared that China and the USA had a very strong collaboration network (f=15). This frequency of network collaboration is followed by the UK and Australia (f=9) and

the USA and Canada ($f=9$). A strong collaboration network between China and Australia ($n=8$) and between China and Canada ($f=7$) is also observed upon the analysis of Figure 9.

3.4. Thematic analysis

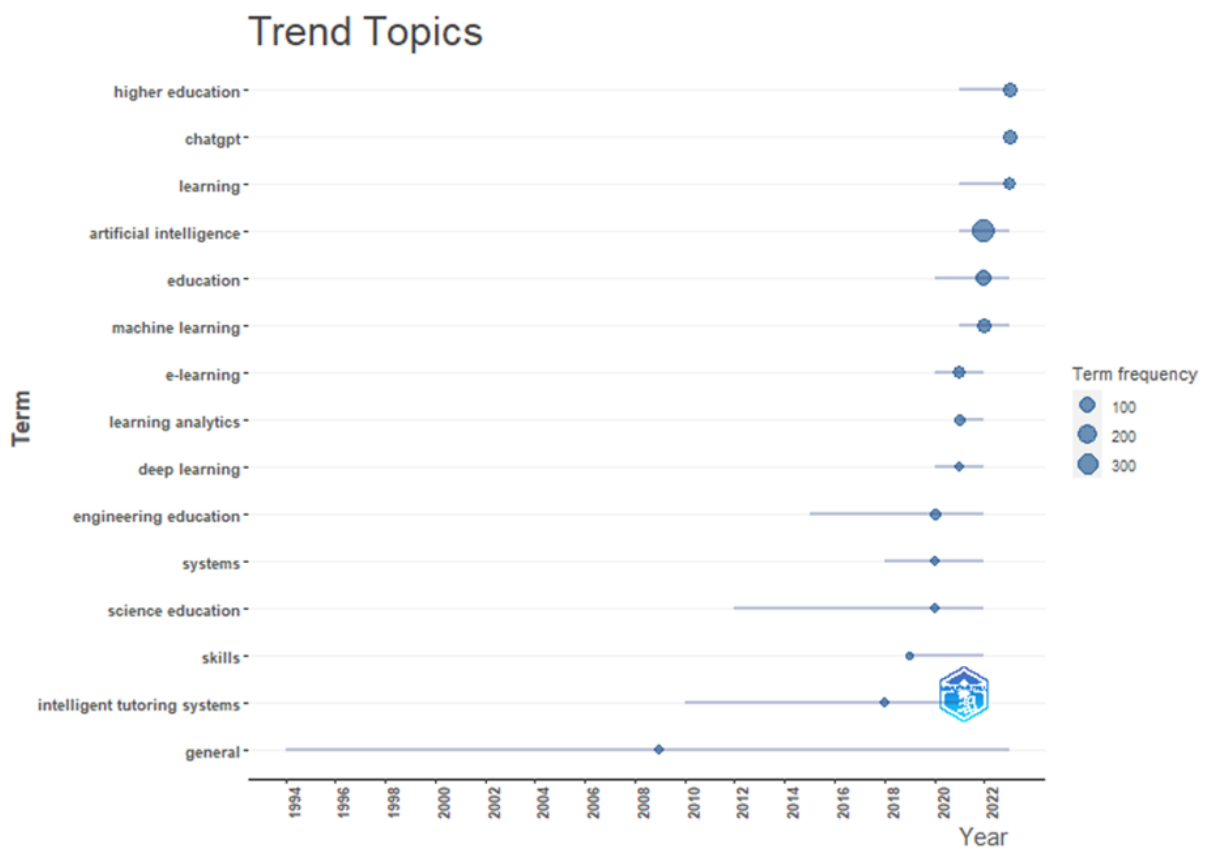
A set of thematic analyses, such as trend topic, thematic map, and co-occurrence network analyses, were also performed. Through these thematic analyses, the recurring themes, clusters, and interconnectedness of various research areas were illustrated.

3.4.1. Trend topics

Figure 10 graphically illustrates the temporal popularity of certain keywords identified by authors over different years. This visualisation focuses on the top three keywords used at least five times per year.

Figure 10

Trend Topics by Author Keywords



The figure above illustrates the trend topics according to author keywords. Until the second decade of the 21st century, the focus was more general, and the publications mostly revolved around intelligent tutoring systems and skills. The analysis suggested that more recently, the authors have narrowed their foci and studied engineering education, science education, systems, e-learning, learning analytics, and deep learning. It is not surprising that during the last three years, artificial intelligence has appeared to be a trending topic. However, interestingly, the focus has shifted from deep learning to machine learning, and studies have specifically concentrated on the context of higher education rather than education in general.

3.4.2. Thematic map

Figure 11 shows a strategic diagram of AIEd research. A strategic diagram shows the interactions of elements of a particular research topic over time. This diagram is a fixed depiction of the network

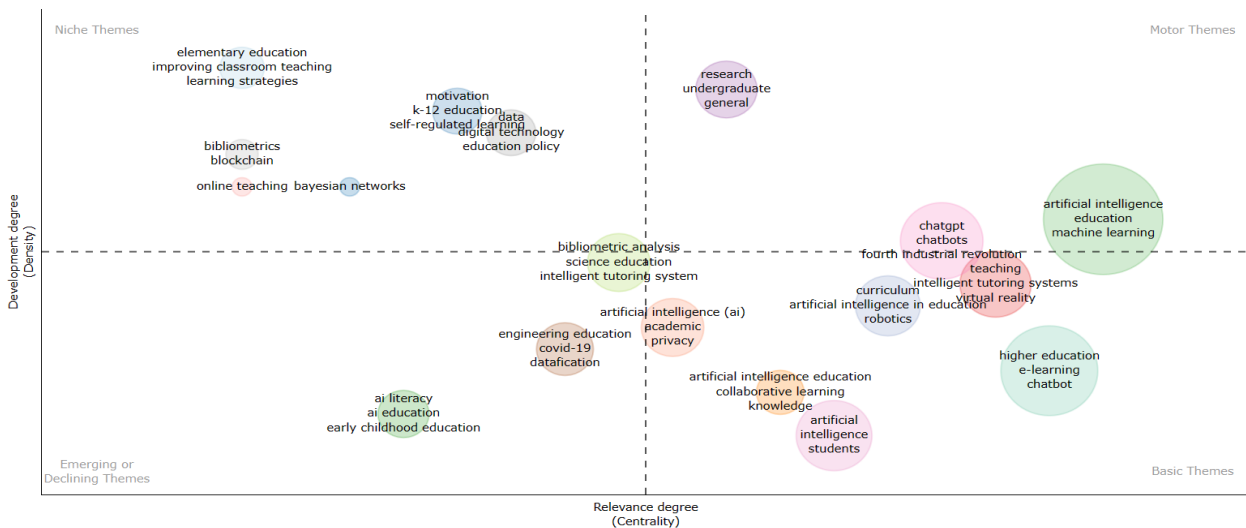
structure of a field. The diagram was created using Bibliometrix by focusing on the top 250 author keywords that appeared at least three to five times. The most common keywords are grouped into themes, each represented by the top three words. The size of each circle in the diagram corresponds to how often that keyword is used.

The strategic diagram was divided into four slices, and each slice was analysed within itself. With this purpose in mind, two metrics, centrality and density, were established. The y-axis represents the intensity parameter, while the x-axis represents the centrality parameter as a thematic map. The greater the centrality of the chosen theme is, the more important it is considered to be; similarly, the higher its intensity is, the more it is regarded as developed (Metli, 2023; Nasir et al., 2020).

In the interpretation of the strategic diagram, Cobo et al. (2011) use the terms Motor, Niche, Emerging or Declining, and Basic Themes. The Motor Themes are characterised by high density and centrality. They indicate significant development in the field of study and are shown in the first quadrant theme, positioned in the upper-right section of the thematic map. The niche themes, denoting highly developed yet isolated areas with high density and relatively lower centrality, align with the second quadrant theme, which is situated in the upper-left part of the thematic map. The emerging or declining themes, which display emerging or declining trends with low centrality and density, correspond to the third quadrant themes located in the lower-left segment of the thematic map. The Basic Themes, extensively researched with well-established internal connections demonstrating low intensity but high centrality, represent the fourth quadrant themes positioned in the lower-right portion of the thematic map. Figure 8 below visualises the interactions of themes related to AIED over time.

Figure 11

Thematic Map



It becomes evident that within the field of education, artificial intelligence has attracted the interest of researchers across various subjects or areas. The largest bubble is observed in the motor theme quadrant, which consists of artificial intelligence, education, and machine learning. These findings suggest that these are the most commonly used author keywords and highly developed themes. In addition, research, undergraduate, and general themes encompass another cluster with high density within the motor themes. Although the ChatGPT, chatbot, and fourth Industrial Revolution clusters are situated mostly within the motor themes quadrant, a small part of these clusters fall into the basic themes quadrant. This observation might indicate that this cluster of ChatGPT, chatbots, and the fourth industrial revolution likely began to receive substantial attention and scrutiny within the field of study. Another basic theme appears to consist of artificial intelligence, academics, and privacy based on the

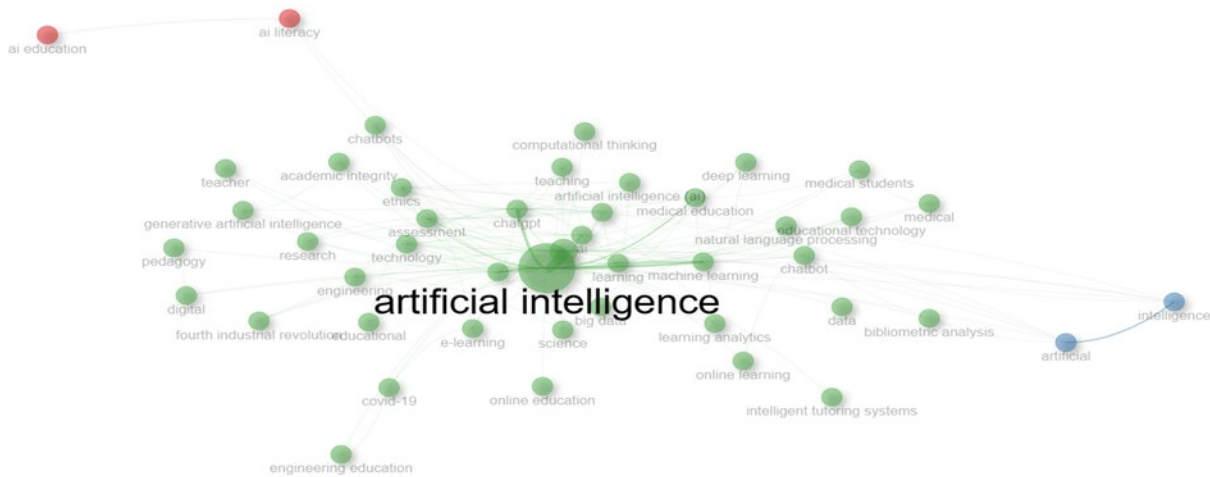
authors' keywords. However, this cluster positions itself on the verge of the basic theme quadrant, indicating that it has a tendency to fall into the emerging and declining themes. Among the emerging or declining themes, the cluster of "engineering education", "COVID-19", and "datafication" was detected, which suggested that although these themes were once well researched, they have started to lose popularity. When the niche themes are analysed, bibliometrics and blockchain; motivation, K-12 education, and self-regulated learning; elementary education; improving classroom teaching; and learning strategies form different clusters.

3.4.3. Co-occurrence network

Co-occurrence network analysis denotes how often two keywords co-occur within an article. This approach helps identify relationships and patterns within the field. Figure 12 shows the results of the co-occurrence network analysis based on author keywords.

Figure 12

Co-Occurrence Network



Upon analysing Figure 12, it can be inferred that the term artificial intelligence dominates the field. It can also be suggested that the term artificial intelligence developed strong links with several other themes, such as machine learning, deep learning, and computational thinking. In addition to the dominating theme, small clusters can be observed. Among those small groups, AI education and AI literacy appeared to be connected, and artificial and intelligence terms were observed to form a different network.

4. Discussion

The current study aimed to gain insight into and graphically represent the body of literature concerning AIEd through the use of the scientific mapping method. The timeframe of the review spans from 1989 to 2023. The last search was conducted in November 2023. The Bibliometrix program in R Software was used to analyse the data. The analysis included the basic structure encapsulating the authors involved in the field, the numbers of publications and references, the annual growth rate, and the average citations per year. The leading countries in the field, their collaborations with other countries, the most influential authors, and their contributions were also analysed. Finally, thematic analysis, including trend topic, cluster, and interconnectedness, of various research areas was also performed.

The main data analysis revealed that 905 documents were published in 271 publication outlets and indexed in the WoS database between 1989 and 2023. A cumulative count of 2,660 different author keywords was recorded. Moreover, the bibliographies included a total of 36,537 articles. The calculated

annual article growth rate is 18.7%, indicating a significant and swift increase in article production over the years. This rapid increase in publications in the field of AIEd is in line with the findings of the current literature (Metli, 2023; Prahani et al., 2022). This swift increase in AIEd publications can be attributed to several reasons. It can be suggested that advancements in technology constitute a main catalyst for the proliferation of publications. Technological developments, specifically in machine learning, deep learning, and natural language processing, paved the way for researchers to explore the field in depth (Song & Wang, 2020).

This study revealed that China, the USA, the UK, Australia, and Spain are the most productive and influential countries in the field of AIEd. Compared to previous studies, it is interesting to observe some variations in the rankings. For example, in Talan's (2021) study, the sequence followed the order of the USA, the UK, China, Australia, and Spain. In turn, Metli's (2023) study portrayed India, rather than Spain, as among the most active countries in the field, although the top four countries were the same in all three studies. When the collaboration world map is analysed, a robust network among the leading countries is observed. While the presence of this strong network is not entirely unexpected, the notable inclusion of Canada, as opposed to Spain, within the scope of collaborative connections is intriguing. The existence of Canada within this network link resonates with the current body of literature. In their relatively narrow-scope study, Baek and Doleck (2020) analysed 135 documents that were published in one journal, namely, the *Journal of Artificial Intelligence in Education*, between 2015 and 2019. Their findings revealed a robust collaborative linkage between the USA and Canada. Furthermore, the findings also revealed the five most influential authors in the field, one of whom appeared to be Hwang GJ. Although Hwang GJ was found to be the second most relevant author in the present study, in Metli's (2023) analysis, he was the most relevant author. This relatively small discrepancy between the current study and that of Metli (2023) might have occurred due to differences in the parameters used during the analysis. Despite this small difference in ranking, it can be concluded that Hwang GJ contributed enormously to the field and is one of the most, if not the most, influential authors in the AIEd field. The analysis of author productivity revealed that the results align with Lotka's Law. This means that although the AIEd has garnered researchers' interest substantially, the majority of them published only one article. The percentage of prolific authors, defined in this study as those who contributed to at least five publications, was calculated as 0.64. These results suggest that although the field has been explored by many researchers, only a few have specialised in this topic. However, while interpreting this finding, it is important to acknowledge the implications for funding allocation, research collaboration, and the challenges in ensuring equity and recognising contributions among researchers in a field.

The most cited works in the field of AiEd are Garcia's (2007) "Evaluating Bayesian networks' precision for detecting students' learning styles", Chuo's (2003) "Redefining the learning companion: the past, present, and future of educational agents", and Goralski's (2020) "Artificial intelligence and sustainable development". These studies suggest that AI in education enhances personalised learning, improves educational outcomes, and supports sustainable and inclusive educational practices. Assessing the role and impact of AI in education, these studies show that AI promotes personalised learning in educational processes, which can better respond to the individual needs of students. This contributes to a more effective and engaging learning experience for students (Liu et al., 2022; Seo et al., 2021). In addition, there is a large body of research supporting that AI-supported educational applications improve educational outcomes and increase students' achievement levels (Chen et al., 2020; García-Martínez et al., 2023). Finally, AI is also frequently researched to support sustainable and inclusive educational practices (Holmes, 2021; Lee & Lee, 2021). Studies on these topics point to the potential to increase equality of opportunity in education and meet the needs of diverse student groups. Hence, it can be inferred that these studies on the importance and impact of AI-supported educational practices shed light on the future development of educational systems. They also provide insights into the versatility and potential of AI in education in general.

Another interesting finding was that *The Journal of Education and Information Technologies* is the journal that publishes the most documents in this field. Moreover, the seven journals in the top ten have technology coverage, emphasizing the impact of educational technologies and digital transformation.

On the other hand, *Educational Sciences* stands out as the second journal with the second highest number of studies, indicating that educational sciences are addressed in a wide range. However, what is more striking is that medical education and engineering education themed journals are also in the top ten. This reveals that AI has become a growing research topic not only in general educational technologies but also in specific teaching fields. In particular, it shows how AI is transforming educational processes in technical and applied fields such as medicine and engineering and contributing to the development of innovative teaching methods in these fields.

For the thematic analyses, the recurring themes, clusters, and interconnectedness of several research areas were analysed. An analysis of the trend topics based on author keywords revealed that, at the beginning of the 21st century, the forefront of scholarly attention was on general skills and smart education systems. However, more recently, researchers have shifted their interest noticeably toward a more diverse range of subjects. This shift can be explained by several factors, including but not limited to the swift progress in educational technologies, the advancements in data analytics methodologies, and, consequently, the increase in AI applications. Notably, the dominance of fields such as science education, engineering education, learning analytics, e-learning, and deep learning potentially highlights the increasing significance of scholarly inquiries in these fields. The scholarly focus on advanced technology domains such as AI and deep learning emphasises their transformational potential in education. Furthermore, the growing amount of study on higher education, as opposed to general education, shows how scholarly interests in this field are evolving. These changes indicate a crucial evolution in educational research and reveal potential areas that could significantly influence future educational approaches.

The current study also investigated the evolution of keyword popularity throughout different time periods. The results revealed the evaluation of several themes over time, which became more or less important in different years. The analysis indicated that while the field was affected by current topics such as COVID-19, which once was popular and then lost popularity, certain themes such as machine learning, ChatGPT, and chatbots maintained their popularity. Based on the results, it can also be inferred that despite the existence of a few studies, there is a research gap in the themes of self-regulated learning, K-12 education, improving classroom teaching, and learning strategies. Hence, additional studies need to be conducted in these areas.

Finally, the analysis of co-occurrence networks revealed that AI has developed strong connections with machine learning, deep learning, and computational thinking. These findings align well with the literature (Metli, 2023; Prahani et al., 2022; Talan, 2021). This emphasises the importance of the strong links between these topics in the field of AI and suggests that future research could focus on examining these relationships in more detail.

4.1. Implications, further research, and limitations

This study has multifaceted implications. Among these implications, several key facets merit elaboration. Primarily, the current study refines the research focus by identifying the most influential authors, leading countries, and trend topics and themes in the field. This enables a more focused approach for researchers and practitioners. Gaining insight into the most common and impactful study types and methodologies helps in narrowing the research focus, facilitating more focused studies, and consequently fostering in-depth understandings within the AIED field. Another facet of this study is that it offers insights for educational policy and practice. The current study revealed the most relevant issues within the AIED field. Understanding the key concerns and priorities in the field helps in informing educational policies and practices. Insights gained from this study can assist policymakers, educators,

and curriculum developers in effectively integrating AI technologies into education, which in turn enhances learning experiences and outcomes. Anticipation and preparation for future trends can be listed as another facet of this study. This bibliometric study aimed to map researchers' main lines of focus and identify evolving trends. Hence, this study serves as a tool for anticipating and preparing for future developments within the AIEd field. This study provides a proactive perspective, helping stakeholders predict and adapt to emerging trends, thus maintaining a competitive edge in the ever-changing landscape of AI in education. Finally, this study can be considered a guide for future research. This study offers a guiding framework for future research within the AIEd field. By outlining motor, basic, emerging, and niche themes, this bibliometric study provides valuable guidance to researchers seeking to investigate niches and new avenues within the field.

Although this study offers several valuable insights, it is important to acknowledge its limitations. One of the main limitations of this bibliometric study is the use of a database. The search was limited to the documents that are listed on the Web of Science (WoS). Despite housing a wide range of publications, employing only the WoS database may have constrained the number of potentially relevant publications. Additional research might include the use of other databases. Another limitation is that the current study restricted the documents to be reviewed to Education Educational Research or Education Scientific Disciplines. Some other categories might include studies relevant to the AIEd. Hence, additional categories can be included in further research. However, in this case, a careful screening to exclude and include the publications is suggested.

5. Conclusion

Technological developments, specifically in artificial intelligence, have led to dramatic transformations in conventional education. Hence, it is imperative to explore the integration of AI into educational fields. With this aim in mind, the current study meticulously conducted a comprehensive bibliometric analysis in AIEd and investigated the patterns, trends, and further directions of AI in education. This study carefully examined the publication outputs, collaboration patterns, cluster formations, and evolutionary trends within the field. By leveraging these detailed and multifaceted analyses, this bibliometric study aimed to offer valuable insights into diverse facets of the AIEd field. Moreover, this study sought to underscore future possibilities and directions for this field.

References

- Alam, A. (2021, November). Possibilities and apprehensions in the landscape of artificial intelligence in education. *2021 International Conference on Computational Intelligence and Computing Applications (ICCICA)*, pp.1-8. IEEE. <https://doi.org/10.1109/ICCICA52458.2021.9697272>
- Arslan, K. (2020). Artificial intelligence and applications in education. *Western Anatolia Journal of Educational Sciences*, 11(1), 71-80. Retrieved from <https://dergipark.org.tr/en/pub/baebd/issue/55426/690058>
- Bearman, M., Ryan, J., & Ajjawi, R. (2023). Discourses of artificial intelligence in higher education: A critical literature review. *Higher Education*, 86(2), 369-385. <https://doi.org/10.1007/s10734-022-00937-2>
- Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). Artificial intelligence trends in education: a narrative overview. *Procedia Computer Science*, 136, 16-24. <https://doi.org/10.1016/j.procs.2018.08.233>
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. *IEEE Access*, 8, 75264-75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Chen, X., Zou, D., Xie, H., Cheng, G., & Liu, C. (2022). Two decades of artificial intelligence in education. *Educational Technology & Society*, 25(1), 28-47. Retrieved from <https://www.jstor.org/stable/10.2307/48647028>
- Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011). An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the Fuzzy Sets Theory field. *Journal of Informetrics*, 5(1), 146-166. <https://doi.org/10.1016/j.joi.2010.10.002>
- Cope, B., Kalantzis, M., & Searsmith, D. (2021). Artificial intelligence for education: Knowledge and its assessment in AI-enabled learning ecologies. *Educational Philosophy and Theory*, 53(12), 1229-1245. <https://doi.org/10.1080/00131857.2020.1728732>
- Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, 20(1), 1-22. <https://doi.org/10.1186/s41239-023-00392-8>
- Cui, W., Xue, Z., & Thai, K. P. (2018). Performance comparison of an AI-based Adaptive Learning System in China. *2018 Chinese Automation Congress (CAC)*, pp.3170-3175. IEEE. <https://doi.org/10.1109/ICCICA52458.2021.9697272>
- García-Martínez, I., Fernández-Batanero, J., Fernández-Cerero, J., & León, S. (2023). Analysing the Impact of Artificial Intelligence and Computational Sciences on Student Performance: Systematic Review and Meta-analysis. *Journal of New Approaches in Educational Research*, 12(1), 171-197. <https://doi.org/10.7821/naer.2023.1.1240>
- Guan, C., Mou, J., & Jiang, Z. (2020). Artificial intelligence innovation in education: A twenty-year data-driven historical analysis. *International Journal of Innovation Studies*, 4(4), 134-147. <https://doi.org/10.1016/j.ijis.2020.09.001>
- Hallinger, P., & Kovačević, J. (2019). A bibliometric review of research on educational administration: Science mapping the literature, 1960 to 2018. *Review of Educational Research*, 89(3), 335-369. Retrieved from <https://www.jstor.org/stable/45277277>

- Hinojo-Lucena, F. J., Aznar-Díaz, I., Cáceres-Reche, M. P., & Romero-Rodríguez, J. M. (2019). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Education Sciences*, 9(1), 51. <https://doi.org/10.3390/educsci9010051>
- Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S., Santos, O., Rodrigo, M., Cukurova, M., Bittencourt, I., & Koedinger, K. (2021). Ethics of AI in Education: Towards a Community-Wide Framework. *International Journal of Artificial Intelligence in Education*, 32, 504 - 526. <https://doi.org/10.1007/s40593-021-00239-1>
- Huang, C., Yang, C., Wang, S., Wu, W., Su, J., & Liang, C. (2019). Evolution of topics in education research: A systematic review using bibliometric analysis. *Educational Review*, 72(3), 281-297. <https://doi.org/10.1080/00131911.2019.1566212>
- İçen, M. (2022). The future of education utilizing artificial intelligence in Turkey. *Humanities and Social Sciences Communications*, 9(1), 1-10. <https://doi.org/10.1057/s41599-022-01284-4>
- İşler, B., & Kılıç, M. (2021). The use and development of artificial intelligence in education. *e-Journal of New Media*, 5(1), 1-11. https://doi.org/10.17932/IAU.EJNM.25480200.2021/ejnm_v5i1001
- Knox, J. (2020). Artificial intelligence and education in China. *Learning, Media and Technology*, 45(3), 298-311. <https://doi.org/10.1080/17439884.2020.1754236>
- Lee, H., & Lee, J. (2021). Applying Artificial Intelligence in Physical Education and Future Perspectives. *Sustainability*. <https://doi.org/10.3390/su13010351>
- Liu, Y., Chen, L., & Yao, Z. (2022). The application of artificial intelligence assistant to deep learning in teachers' teaching and students' learning processes. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/fpsyg.2022.929175>
- Lotka, A. J. (1926). The Frequency Distribution of Scientific Productivity. *Journal of the Washington Academy of Sciences*, 16, 317-323. Retrieved from <https://www.jstor.org/stable/24529203>
- Maphosa, V., & Maphosa, M. (2023). Artificial intelligence in higher education: a bibliometric analysis and topic modeling approach. *Applied Artificial Intelligence*, 37(1), 2261730. <https://doi.org/10.1080/08839514.2023.2261730>
- Merigó, J. M., & Yang, J. B. (2017). A bibliometric analysis of operations research and management science. *Omega*, 73, 37-48. <https://doi.org/10.1016/j.omega.2016.12.004>
- Metli, A. (2023). Articles on Education and Artificial Intelligence: A Bibliometric Analysis. *Journal of Social Sciences And Education*, 6 (Education Special Issue), 279-312. <https://doi.org/10.53047/josse.1352197>
- Nasir, A., Shaukat, K., Hameed, I. A., Luo, S., Alam, T. M., & Iqbal, F. (2020). A bibliometric analysis of corona pandemic in social sciences: A review of influential aspects and conceptual structure. *IEEE Access*, 13(8), 133377-133402. <https://doi.org/10.1109/ACCESS.2020.3008733>
- Owoc, M. L., Sawicka, A., & Weichbroth, P. (2019, August). Artificial intelligence technologies in education: benefits, challenges and strategies of implementation. *IFIP International Workshop on Artificial Intelligence for Knowledge Management*, pp.37-58. Springer International Publishing. https://doi.org/10.1007/978-3-030-85001-2_4
- Paul, J., Lim, W. M., O'Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). *International Journal of Consumer Studies*, 45(4), 01-016. <https://doi.org/10.1111/ijcs.12695>

- Prahani, B. K., Rizki, I. A., Jatmiko, B., Suprpto, N., & Amelia, T. (2022). Artificial intelligence in education research during the last ten years: A review and bibliometric study. *International Journal of Emerging Technologies in Learning*, 17(8), 169-188. <https://doi.org/10.3991/ijet.v17i08.29833>
- Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner-instructor interaction in online learning. *International Journal of Educational Technology in Higher Education*, 18, 1-23. <https://doi.org/10.1186/s41239-021-00292-9>
- Song, P., & Wang, X. (2020). A bibliometric analysis of worldwide educational artificial intelligence research development in recent twenty years. *Asia Pacific Education Review*, 21, 473-486. <https://doi.org/10.1007/s12564-020-09640-2>
- Song, Y., Chen, X., Hao, T., Liu, Z., & Lan, Z. (2019). Exploring two decades of research on classroom dialogue by using bibliometric analysis. *Computers & Education*, 137, 12-31. <https://doi.org/10.1016/j.compedu.2019.04.002>
- Sreenivasan, A., & Suresh, M. (2023). Twenty years of entrepreneurship education: A bibliometric analysis. *Entrepreneurship Education*, 6(1), 45-68. <https://doi.org/10.1007/s41959-023-00089-z>
- Swiecki, Z., Khosravi, H., Chen, G., Martinez-Maldonado, R., Lodge, J. M., Milligan, S., Selwyn, N., & Gašević, D. (2022). Assessment in the age of artificial intelligence. *Computers and Education: Artificial Intelligence*, 3, 1-10. <https://doi.org/10.1016/j.caeai.2022.100075>
- Talan, T. (2021). Artificial intelligence in education: A bibliometric study. *International Journal of Research in Education and Science*, 7(3), 822-837. <https://doi.org/10.46328/ijres.2409>
- Xu, W., & Ouyang, F. (2022). A systematic review of AI role in the educational system based on a proposed conceptual framework. *Education and Information Technologies*, 27, 1-29. <https://doi.org/10.1007/s10639-021-10774-y>
- Yu, D., & Shi, S. (2015). Researching the development of Atanassov intuitionistic fuzzy set: Using a citation network analysis. *Applied Soft Computing*, 32, 189-198. <https://doi.org/10.1016/j.asoc.2015.03.027>
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—where are the educators?. *International Journal of Educational Technology in Higher Education*, 16(1), 1-27. <https://doi.org/10.1186/s41239-019-0171-0>

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Determination of Teachers' Perceptions of Artificial Intelligence Concept: A Metaphor Analysis

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Abstract: This research sought to explore educators' views on Artificial Intelligence (AI), a topic that has become increasingly important with the advent of recent digital transformations. Given its potential impact on education, AI can offer valuable insights for curriculum planning and teaching strategies. The study used metaphor analysis to understand educators' perspectives on AI. An online questionnaire was employed to collect data from teachers working in schools affiliated with the Ministry of National Education in Şanlıurfa in the 2023-2024 academic year. Teachers were asked to complete the sentences about their perceptions of artificial intelligence, especially using expressions such as "Artificial intelligence is like ..." and "...because ...". According to the findings of the metaphor analysis, teachers conceptualized AI as a job facilitator, associating it with robots and machines representing cognitive intelligence. However, concerns also emerged about the potential risks of AI and its impact on creativity. The findings emphasized the complex perceptions of AI in education, showcasing the balance between its positive contributions and the ethical responsibilities it entails. While the study offers valuable insights for understanding the complexity of AI in the educational context, it also highlights the various metaphors teachers use to describe this technology. In this context, prominent metaphors used by teachers to describe artificial intelligence include human, robot, brain, assistant, and machine.

Keywords: Metaphor Analysis, Artificial Intelligence, Teacher Perception, Educational Technology

1. Introduction

In today's world, where each scientific advancement accelerates the next invention, new technologies are becoming indispensable at every stage of our lives. Alongside the advancing technology, significant developments are also occurring in our education system. As noted by Wildman and Niles (1987), the success of change and development efforts in educational institutions depends on the management's understanding within those institutions. This understanding has imposed new responsibilities on school administrators and teachers who play a crucial role in integrating technology into education (Akbaba, 2002; Anderson & Dexter, 2005; Flanagan & Jacobsen, 2003).

Artificial Intelligence (AI) is one of the most important technologies of our time. Today, we encounter AI and its applications not only in industry but also in almost every field from agriculture to health, from voice assistants to online chat and communication. Consequently, AI is gaining significance in the field of education with each passing day. According to the 2018 Horizon report, AI and adaptive learning technologies stand out as important developments in the field of educational technology (Becker et al., 2018). Similarly, the 2024 Horizon Report sees AI as a catalyst for significant advances in higher education, noting that it can enhance learning experiences, but also posing challenges that require careful management and ethical consideration (Pelletier vd., 2024).

In its simplest definition, intelligence is the ability to interpret external stimuli, transform them into information, and use them. The fact that computers show human-like behaviors such as reasoning, problem-solving, inference, and generalization, that is, the use of high-level cognitive skills, can be

defined as AI (Arslan, 2020). Today, when AI studies related to education are examined, not only knowledge-based but also data and logic-based AI applications take place in every field. Among these areas, applications that contribute directly to school management and indirectly to teaching such as personalized education systems, exploratory education, student essay analysis, automatic test creation systems, exam management, course schedules, and staff schedules are the first ones that come to mind (Holmes et al., 2019).

The success of AI education is closely related to teachers' knowledge and perceptions of AI, and it is also important to understand how prepared teachers are (Ayanwale et al., 2022). There are various ways to express mental perceptions. One of these is "metaphors" (Kösterelioğlu, 2014).

Güneş and Fırat (2016) highlighted that metaphor analysis can be used when traditional data collection tools such as interviews and observations cannot be used. According to the mental metaphor theory, metaphor can be defined as evaluating a phenomenon or event according to another phenomenon or event (Lakoff & Johnson, 1980).

According to Saban (2009), metaphor is formed by stating that a phenomenon X is like a phenomenon Y and this is what makes metaphor powerful as a mental model. Morgan (1980) characterized the use of metaphor as a way of thinking and a way of seeing our perception of the world, and in this respect, metaphors enable the individual to perceive a certain phenomenon as another phenomenon by directing the individual's mind from a certain way of comprehension to another way of comprehension.

Arslan and Bayrakçı (2006) described metaphor as a powerful mental mapping and modeling mechanism for individuals to understand and structure their world. Recently, studies on artificial intelligence and metaphor have gained importance in national and international education.

This study aimed to explore teachers' complex mental perceptions of artificial intelligence through metaphor analysis. As key stakeholders in the educational environment, teachers' perspectives on this transformative technology have significant implications for its effective and ethical implementation in the classroom. By identifying the various metaphors teachers use to conceptualize AI, this study provides insight into the multifaceted ways in which they make sense of this emerging technology and its potential impact on teaching and learning. By using the metaphor method to explore the complex interplay between teachers' beliefs, concerns, and aspirations regarding integrating AI into education, we aim to contribute to the literature with an in-depth examination of these metaphors.

1.1 Literature review

Metaphor studies have been used in various studies to address the perceptions of school administrators, teachers, pre-service teachers, and students in education (Kalaycı, 2018; Koç Akran & Karakaş, 2023; Sabahat et al., 2023). While Kalaycı's (2018) study explored the perceptions of primary school students toward 'science' and 'science' courses, Sabahat et al.'s (2023) study aimed to understand the perceptions of students, teachers, and school administrators toward the changing concept of school during the COVID-19 pandemic through metaphor analysis method. Similarly, Koç Akran and Karataş (2023) studied the perceptions of pre-service teachers towards Generation Z by using metaphor analysis in their study.

There is a limited number of metaphorical analysis studies directly related to the concept of Artificial Intelligence (AI), but metaphorical analyses of concepts such as the internet, technology, and computers, which are related to this concept, which is an output of digital transformation, are very common (Akçin, 2023; Ekici, 2016; Kaleli Yılmaz & Güven, 2015; Lindh & Nolin, 2017). The studies conducted by Akçin (2023) on robotic coding; Ekici (2016) on the concept of computers; Kaleli Yılmaz and Güven (2015) on distance education; and Lind and Nolin (2017) on the development of cloud technology through

participants' metaphorical conceptualizations point to the diversity of the ways individuals conceptualize and make sense of the internet, robotic coding, cloud technology, and distance education through metaphors.

There are various metaphor analysis studies on AI at different levels and in different forms (Aydın et al., 2022; Demir & Güraksin, 2022; Saçan et al., 2022). Aydın et al. (2022) prepared computer-assisted animations for teaching the concept of AI based on the opinions of information technologies teachers and evaluated how these animations affected fifth-grade students' perceptions of AI. Demir and Güraksin (2022) examined middle school student's perceptions of the concept of AI with the metaphorical analysis method. Saçan et al. (2022) applied metaphorical analysis to the idea of AI for children between the ages of 6-10 and their parents. In this study, unlike student perceptions of the concept of AI, which was put on the agenda by the Ministry of National Education (MoNE) in parallel with the public opinion created by the introduction of ChatGPT by OpenAI company in 2022 (Ministry of National Education, 2023), teacher perceptions were addressed through metaphors.

The study concluded that a significant portion of children learned about artificial intelligence from media tools, therefore children should be introduced to the concept of artificial intelligence appropriately and correctly from an early age, and parents should also be made aware of artificial intelligence.

1.2 Purpose of the research

The study aimed to examine the perspectives of educators on the concept of AI, which has gained importance with digital transformations in recent years, through the metaphor analysis method. For this purpose, answers to the following questions were sought:

- What are the metaphors generated by teachers about the concept of AI?
- Under which conceptual categories are the metaphors produced by teachers grouped?

2. Method

A phenomenological research method was used to examine teachers' perceptions of the concept of AI. Phenomenology is a qualitative research method that examines the experiences of individuals and how these experiences are perceived (Moustakas, 1994). In this context, the metaphor analysis method was adopted to understand the participants' perceptions. Metaphor analysis is a method used to identify and analyze metaphors in a text and allows for a deeper understanding of the conceptual structures and cognitive patterns underlying the text (Güneş & Fırat, 2016). In the context of a phenomenological study, metaphor analysis provides a deeper understanding from the perspective of those who experience the phenomenon by focusing on how metaphors capture the essence of the experiences under study. This method is based on the premise that metaphors are not only a figure of speech, but also a fundamental mental mechanism that affects the way individuals perceive and interpret the world (Lakoff & Johnson, 1980).

2.1 Participants

The participants were teachers working in Şanlıurfa in the 2023-2024 academic year. To reach the teachers working in the study, convenience sampling, one of the purposeful sampling methods, was used. In this sampling type, researchers choose this sampling type because they can easily reach a certain community (Yıldırım & Şimşek, 2016). 295 teachers participated in the study and 9 teachers did not complete the form because they did not approve the consent form. 22 teachers' views on AI were not included in the evaluation since they did not describe the metaphor. When the metaphor is not

defined, the metaphor may be misinterpreted. Demographic information of 264 teachers who were evaluated for the study is given in Table 1.

Table 1*Demographic Information of Teachers*

		f	%
Gender	Female	123	46,6
	Male	141	53,4
Education	Associate Degree	1	0,4
	Undergraduate	219	83,0
	Master's degree	41	15,5
	PhD	3	1,1
Experience	1-5 Years	69	26,1
	6-10 Years	67	25,4
	11-15 Years	52	19,7
	16-20 Years	29	11,0
	21-25 Years	31	11,7
	26 Years and Above	16	6,1
Grade	Preschool	11	4,2
	Primary School	70	26,5
	Secondary School	118	44,7
	High School	57	21,6
	Other	8	3,0

According to Table 1, 46.6% of the teachers participating in the study were female and 53.4% were male. In this context, many of the teachers participating in the study were male. An analysis of the level of education showed that the majority of the teachers (83.0%) had a bachelor's degree. In terms of seniority, most of the teachers (26.1%) had 1-5 years of experience and (25.4%) had 6-10 years of experience, this shows that more than half of the teachers have less than 10 years of experience. In addition, the majority of the teachers participating in the study worked at the secondary school level (44.7%). The distribution of the teachers participating in the study according to their branches is given in Table 2.

Table 2*Distribution of the Teachers Participating in the Study According to their Branches*

Branch	f	%	Branch	f	%
Primary School Teacher	56	21.2	Visual Arts Teacher	5	1.9
Science Teacher	25	9.5	Imam Hatip High School Vocational Teacher	4	1.5
Elementary Mathematics Teacher	21	8.0	Music Teacher	4	1.5
Turkish-Language Teacher	19	7.2	Biology Teacher	4	1.5
Religious Culture and Moral Knowledge Teacher	17	6.4	Arabic Teacher	3	1.1
English Teacher	15	5.7	Chemistry Teacher	3	1.1
Guidance Teacher	14	5.3	Technology and Design Teacher	2	0.8
Social Studies Teacher	11	4.2	French Teacher	2	0.8
Preschool Teacher	10	3.8	Geography Teacher	2	0.8
Physical Education Teacher	8	3.0	Child Development Teacher	2	0.8
Special Education Teacher	8	3.0	Physics Teacher	1	0.4
Turkish Language and Literature Teacher	8	3.0	Electricity Teacher	1	0.4
Other	6	2.3	Philosophy Teacher	1	0.4
History Teacher	6	2.3	Secondary Mathematics Teacher	1	0.4
Information Technology Teacher	5	1.9			
			Total	264	100.0

Table 2 presents the distribution of the teachers participating in the study according to their branches. According to the analysis, the majority of the teachers participating in the study (21.2%) were identified as primary school teachers, and they were followed by science teachers with 9.5%. The lowest participation rate belongs to Physics, Electricity, Philosophy, and Secondary Mathematics teachers with 0.4%. Although the participation of teachers from different branches in the study enables different perceptions of AI, the difference in the number of participations based on the branch is one of the limitations of the study.

2.2 Data collection and data analysis

Studies in the literature were examined in the development of the data collection tool (Bozkurt, 2020; Hacifazlıoğlu et al., 2011; Saban, 2009). In line with the reviewed studies, a semi-structured interview form was developed. The semi-structured interview form consists of two parts. The first part includes the section where data on teachers' demographic information (gender, education level, seniority, school level, and branch) will be collected, and the second part is the section where data on teachers' metaphorical perceptions are collected. To reveal the metaphorical perceptions of the teachers, each participant was asked to complete the construct 'Artificial Intelligence is like.....because.....' related to the concept of Artificial Intelligence. Participants were also asked to define a metaphor. The concept of 'like' in this structure aimed to establish a connection between the subject and the source of the metaphor. In addition, the concept of 'because' was used to reveal the justification attributed to the metaphor (Saban, 2008, 2009). This form was integrated into an online environment and data were collected from teachers through the online environment.

Data were collected through an online environment. The content analysis method was used to analyze the qualitative data collected for metaphorical perception (Yıldırım & Şimşek, 2016). Metaphors were created through content analysis and these metaphors were grouped under categories. Frequencies and percentages were used to show the frequency of use of metaphors. Data analysis was carried out in four stages (Saban, 2004):

1. Analyzing and evaluating the collected data: At this stage, the data collected through the online environment were exported in Microsoft Excel format and the data were put in an order after numbering.
2. Sorting stage and creation of metaphors: At this stage, metaphors that were irrelevant or invalid were eliminated from the data transferred to MAXQDA software. 22 teachers' opinions about AI were not included in the evaluation because they did not describe the metaphor. When the metaphor is not defined, the metaphor may be misinterpreted. Metaphors were produced by coding from the opinions included in the evaluation.
3. Creating categories from the metaphors: At this stage, the metaphors created on the MAXQDA application were grouped under categories. This involves a systematic process of reviewing each metaphor and identifying recurring concepts. Metaphors with similar ideas are then grouped under relevant categories.
4. Validity and reliability procedures: At this stage, coding was performed by a second expert and Cohen's Kappa value was calculated through MAXQDA software. Kappa value was found to be 0.89. This value being in the range of 0.81-1.00 is considered a "very good agreement" (Kılıç, 2015). To contribute to the validity and reliability of the research, the opinions of the participants were given using abbreviations such as T-1, T-2 without specifying the names of the participants.

Ethical Approval: Ethics committee approval dated 19.10.2023 and numbered 2023/156 was obtained from Harran University Social and Human Sciences Ethics Committee for this research.

3. Findings

In this part of the study, the findings of the data collected from the teachers regarding the concept of AI are discussed in the context of the research questions respectively.

3.1 What are the metaphors produced by teachers about the concept of AI?

In this section, the metaphors produced by the teachers about the concept of AI are included. The data includes the metaphors used by the teachers to define AI during the research process. Table 3 presents the metaphors produced by teachers to express the concept of AI.

Table 3

Teachers' Metaphors about the Concept of AI

No	Metaphor Name	f	No	Metaphor Name	f	No	Metaphor Name	f
1	Human	26	36	Miracle	2	71	Tightrope Walking	1
2	Robot	25	37	Ocean	2	72	Swiss Army Knife	1
3	Brain	13	38	Player	2	73	Heart	1
4	Assistant	10	39	Compass	2	74	Commander	1
5	Machine	10	40	Dream	2	75	Sheep	1
6	Space	9	41	Soil	2	76	Remote Control	1
7	Computer	8	42	Artificial Flower	2	77	Bird	1
8	Baby	7	43	Star	2	78	Small Home Appliances	1
9	Intelligence	6	44	Time	2	79	Lemon	1
10	Future	5	45	Octopus	1	80	Logic	1
11	Teacher	5	46	Gold	1	81	Scapel	1
12	Technology	5	47	Key	1	82	Nur	1
13	Light	4	48	Encyclopedia	1	83	Nuclear Energy	1
14	Weapon	4	49	Antidepressant	1	84	Spider	1
15	Car	3	50	Search Engine	1	85	Daisy	1
16	Mirror	3	51	Horse	1	86	Potato	1
17	Wise	3	52	The Unknown Path	1	87	Spring	1
18	Digital Universe	3	53	Plant	1	88	Renaissance	1
19	Parent	3	54	Chameleon	1	89	Clock	1
20	Hand Foot	3	55	Puzzle	1	90	Milky Way Galaxy	1
21	Imagination	3	56	Cloud	1	91	Cigarette	1
22	Medicine	3	57	The Invisible Part of the Iceberg	1	92	Magic Wand	1
23	Tree	2	58	Counselor	1	93	Simulation	1
24	Aladdin's Genie	2	59	Mill	1	94	Glossary	1
25	Fire	2	60	State	1	95	Chief	1
26	Moon	2	61	Bottomless Well	1	96	Savings	1
27	Avalanche	2	62	DNA	1	97	Horizon Line	1
28	Night	2	63	Education Coaching	1	98	Virus	1
29	Shadow	2	64	Idea	1	99	Demigod	1
30	Solar System	2	65	Movie	1	100	Investment	1
31	Copy of Life	2	66	Night and Day	1	101	Cooking	1
32	Animal	2	67	Sky	1	102	Method	1
33	Invention	2	68	Ghost	1	103	Time Machine	1
34	Oracle	2	69	Cell Nucleus	1			
35	Closed Box	2	70	Wrench	1			
					103	Total	264	

According to Table 3, a total of 103 metaphors were produced by teachers. These metaphors were coded 264 times in total. Among the metaphors analyzed, the most coded metaphors were human (26) and robot (25) metaphors, respectively.

3.2 Under which conceptual categories are the metaphors generated by teachers grouped?

In the context of this research question, the metaphors produced by teachers about the concept of AI were categorized. This involves a systematic process of reviewing each metaphor and identifying recurring concepts. Metaphors with similar ideas are then grouped under relevant categories. These categories are given in Table 4.

Table 4

Distribution of the Metaphors Produced by Teachers about the Concept of AI According to Categories

Categories	Metaphors	f
Technology and Machines	Robot (25), Assistant (10), Machine (10), Computer (8), Technology (5), Car (3), Digital Universe (3), Invention (2), Compass (2), Artificial Flower (2), Search Engine (1), Mill (1), Small Home Appliances (1), Nuclear Energy (1), Investment (1), Time Machine (1)	76
Live Assets	Human (26), Baby (7), Parent (3), Hand-Foot (3), Tree (2), Animal (2), Player (2), Octopus (1), Horse (1), Plant (1), Chameleon (1), Sheep (1), Bird (1), Spider (1), Chef (1)	53
Education and Mental Expressions	Brain (13), Intelligence (6), Teacher (5), Wise (3), Imagination (3), Dream (2), Encyclopedia (1), Counselor (1), Educational Coaching (1), Idea (1), Logic (1), Renaissance (1), Simulation (1), Dictionary (1), Savings (1), Method (1)	42
Nature and the Universe	Space (9), Light (4), Fire (2), Moon (2), Avalanche (2), Night (2), Shadow (2), Solar System (2), Ocean (2), Earth (2), Star (2), Time (2), Cloud (1), Night and Day (1), Sky (1), Daisy (1), Spring (1), Milky Way Galaxy (1), Horizon Line (1),	40
Daily Life and Objects	Mirror (3), Copy of Life (2), Gold (1), Key (1), Movie (1), Wrench (1), Tightrope Walking (1), Swiss Army Knife (1), Remote Control (1), Lemon (1), Potato (1), Clock (1), Cooking (1)	16
The Future and the Unknown	The Future (5), The Closed Box (2), The Unknown Path (1), The Puzzle (1), The Invisible Part of the Iceberg (1), The Bottomless Pit (1)	11
Magical and Imaginary Elements	Aladdin's Genie (2), Oracle (2), Miracle (2), Ghost (1), Light (1), Magic Wand (1), Demigod (1)	10
Health	Drug (3), Antidepressant (1), DNA (1), Cell Nucleus (1), Heart (1), Scalpel (1), Cigarette (1)	9
Security	Weapon (4), State (1), Commander (1), Virus (1)	7

In Table 4, the metaphors created by the teachers for the concept of AI are grouped under certain categories. These metaphors were classified under 9 different categories in total. The highest number of metaphors and coding occurred in the Technology and Machines category ($f=76$). The lowest number of metaphors was found in the category of Security, with a total of 7 codings in this category. In the context of this research question, the categories presented in Table 4 are explained below under the headings respectively.

3.3 Technology and machines category

As seen in Table 4, 16 metaphors were created under this category, in particular, metaphors such as the robot, assistant, machine, and computer stand out in this category. Teachers perceive Artificial Intelligence as a programmable and automatically functioning entity, thinking of it as a robot.

Sample participant views:

Artificial Intelligence is just like a robot because robots are also directed by others (T-51).

Artificial Intelligence is like a machine because it makes our work easier (T-1).

Artificial Intelligence is like an assistant because it helps us in every subject (T-93).

Artificial Intelligence is like a computer because it can search, learn, and apply every piece of information (T-245).

3.4 Live assets category

According to Table 4, a total of 15 metaphors were created under this category, and metaphors such as human, baby, parent, hand-foot, tree, and animal are at the forefront in this category. These metaphors were coded 53 times in total and focused on associating AI with living beings and equipping it with human-like features.

Sample participant views:

Artificial Intelligence is like a human who uses 100% of his/her brain because it has the potential and energy to do all kinds of creativity (T-117).

Artificial Intelligence is like a newborn baby because it learns what we teach. If we teach good things, he takes it, if we teach bad things, he grasps it. He adopts our way of life and culture and exhibits behavior accordingly (T-109).

Artificial Intelligence is like foster parents because protective parents guide cautious behavior with their predictions (T-77).

Artificial intelligence is like a hand and foot because it helps us fulfill our needs (T-66).

3.5 Education and mental expressions category

A total of 16 metaphors were produced under this category (Table 4): metaphors such as brain, intelligence, teacher, and wise stand out in this category. These metaphors were coded 42 times in total and associated with the mental and educational aspects of AI.

Sample participant views:

Artificial Intelligence is like an artificial brain because if it is used correctly, it works like a brain (T-242).

Artificial Intelligence is like human intelligence because many things that are done with human intelligence are imitated in a way to makes different beings capable of doing them (T-202).

Artificial Intelligence is like a teacher because it makes our lives easier and enables us to obtain information that is more difficult to obtain more easily (T-76).

Artificial Intelligence is like a sage who knows everything. Because whatever you ask, it has an idea (T-145).

3.6 Nature and the universe category

A total of 19 metaphors were generated in this category (Table 4), with notable examples including space, light, moon, avalanche, and night. These metaphors were coded 40 times in total, emphasizing the comparison of AI to elements in the universe and nature.

Sample participant views:

Artificial Intelligence is like space because it is full of unknowns and surprises (T-107).

Artificial Intelligence is like light because light enlightens us and artificial intelligence enlightens us (T-17).

Artificial Intelligence is like the moon because the moon reflects the sunlight and artificial intelligence uses the example of human beings (T-181).

Artificial Intelligence is like an avalanche because as it progresses, it causes new growth (technological) in every field (T-168).

3.7 Daily life and objects category

A total of 13 metaphors were generated in this category (Table 4), with prominent examples including mirror, copy of life, gold, and key. These metaphors were coded 16 times in total, focusing on the association of AI with everyday life and objects.

Sample participant views:

Artificial Intelligence is like a mirror because we see ourselves in front of it (T-58).

Artificial intelligence is like a copy of life because it is similar to the things in life, it is the reflection of life to us with slight changes (T-262)

Artificial intelligence is like a key because it opens the door to new worlds (T-271)

Artificial intelligence is like a lemon because it looks good and smells nice but it is sour in the mouth. Artificial intelligence is also good to use, but if it is not used correctly, it will harm people. (T-63)

3.8 Future and the unknown category

A total of 6 metaphors were produced under this category (Table 4), metaphors such as future, closed box, and unknown road stand out in this category. These metaphors were coded 11 times in total, emphasizing the uncertainty and unexplored potential of AI for the future.

Sample participant views:

Artificial Intelligence is like a future full of secrets because the benefits it will provide to humanity cannot even be predicted yet. (T-35)

Artificial Intelligence is like walking on an unfamiliar path because walking on the road is exciting and scary. (T-216).

Artificial Intelligence is like a puzzle because as you solve it, your mind opens (T-36).

Artificial Intelligence is like the invisible part of the calf because I think that we have discovered very few things that can be done with artificial intelligence (T-7).

3.9 Magical and imaginary elements category

A total of 7 metaphors were produced under this category (Table 4), metaphors such as Aladdin's Genie, clairvoyant, and miracle stand out in this category. These metaphors were coded 10 times in total and focused on the association of AI with magical and imaginary elements.

Sample participant views:

Artificial Intelligence is like Aladdin's Genie because it offers us what we want immediately (T-188).

Artificial Intelligence is like a soothsayer because it predicts the next step (T-141)

Artificial Intelligence is like a miracle because artificial intelligence is something that affects and facilitates our lives just like miracles, it is something that has no limits, and just as new miracles can happen at any moment, artificial intelligence is renewable (T-210).

Artificial intelligence is like a ghost because it does not have a certain shape and weight. It does not occupy space, but it frightens humanity (270, Location 1-2)

3.10 Health category

A total of 7 metaphors were produced under this category (Table 4), metaphors such as drugs, antidepressants, and DNA stand out in this category. These metaphors were coded 9 times in total, emphasizing the role and effects of AI in health.

Sample participant views:

Artificial Intelligence is like medicine because what determines whether it is useful or harmful is its correct use (T-116).

Artificial Intelligence is like an antidepressant because when the dosage is not adjusted well, it gets out of control (T-102).

Artificial Intelligence is like a DNA helix because as you enter into it, endless new information welcomes you. (T-126)

Artificial Intelligence is like a scalpel because if you give the scalpel to a doctor, it will save a person's life, but if you give it to a tramp, it will ruin both his life and someone else's life (T-244)

3.11 Security category

A total of 4 metaphors were produced under this category (Table 4), metaphors such as weapon, state, and commander stand out in this category. These metaphors were coded 7 times in total and focused on associating AI with security and assuming a controlling role.

Sample participant views:

Artificial Intelligence is like a weapon because it kills people's brains (T-59).

Artificial Intelligence is like a commander because it orders the commands that the brain will receive to its systems in its format like the functioning of the human mind (T-236).

Artificial Intelligence is like a state because you know its existence but you cannot touch it (T-32).

Artificial Intelligence is like viruses because it will enter our lives suddenly and when it becomes strong enough, it will take control and threaten the existence of the human species (T-172).

After categorizing the metaphors from 264 teachers in total within the scope of the research, it presents a word cloud focusing on the most coded metaphors in each category. The most coded metaphors among the categories analyzed in detail in this section are highlighted in Figure 1 with the word cloud.

Figure 1

Word Cloud Representation of Teachers' Most Frequently Coded Metaphors Related to the Concept of AI



The word cloud in Figure 1 visually expresses the most prominent metaphors coded at least twice for each category and the frequency of these metaphors. This visual provides an important summary to determine teachers' perceptions of the concept of AI.

4. Discussion and Conclusion

The findings show that teachers use various metaphors to understand and define the concept of AI. The findings also show that teachers generally associate AI with technology and machines, but they also evaluate this concept under different categories. These categories include "Living Beings," "Education and Mental Expressions," "Nature and Universe," "Daily Life and Objects," "Future and Unknown," "Magical and Imaginary Elements," "Health," and "Security."

Among the prominent metaphors in the technology and machines category are technological terms such as "Robot," "Assistant," "Machine," and "Computer". Teachers perceived Artificial Intelligence as a programmable and automatically functioning entity. When these perceptions are supported with examples from teachers' opinions, metaphors can be explained in a more meaningful way. For example, "Artificial Intelligence is just like a robot. Because robots are also directed by others" (T-51). Similarly, metaphors such as robot, machine, and computer were frequently used in studies conducted with different target groups in the literature (Aydın et al., 2022; Demir & Güraksin, 2022; Saçan et al., 2022).

In the category of Living Beings, teachers associated AI with living beings such as "Humans," "Baby," "Parents," "Hand-Foot," and "Animals". These metaphors tend to equip AI with human-like characteristics. Excerpts from the teachers' views explain how teachers understand AI by underlining these metaphors. For example, "Artificial Intelligence is like a human who uses 100% of his/her brain. Because it has the potential and energy to do all kinds of creativity" (T-117). Similarly, in Aydın et al.'s (2022) study, both the human metaphor was used and the human category was created. Additionally,

this study included metaphors like baby and plant. This finding is also supported by the research of Demir and Güraksin (2022) and Saçan (2022).

The use of metaphors in understanding and explaining the concept of Artificial Intelligence offers deep insight into how teachers perceive and make sense of this advanced technology. By associating AI with living beings, everyday life, objects, and even magical/imaginary elements, teachers can convey a wide range of features and implications of AI. This diversity allows teachers to make sense of AI in their context and bring different perspectives to this concept. Teachers' perspectives taken in this context play a crucial role in curriculum planning (Chiu & Chai, 2020), promoting students' well-being (Dai et al., 2020), and improving teaching effectiveness (Lin, 2022). Moreover, teachers' attitudes toward AI influence the reliability of educational research evidence (Cukurova et al., 2020) and their confidence in AI-enabled educational technology (Nazaretsky et al., 2022). Moreover, teachers' perceptions influence the development of AI literacy (Zhao et al., 2022), the design of AI-supported pedagogical actions (Kasepalu et al., 2022), and the investigation of the impact of AI on teaching and learning (Bearman et al., 2023). The study emphasizes that these diverse metaphors are a valuable resource for understanding the role and potential implications of AI in education. The diverse interpretations of AI can assist educators in adopting this technology more efficiently and effectively imparting its knowledge to students. However, the study's focus on examining teachers' perspectives on AI in a specific region may have limited the coverage of all potential perspectives on AI in education. Additionally, the use of a sentence completion method could have influenced teachers' metaphor choices, potentially restricting the diversity of viewpoints expressed.

Future research could examine AI-related metaphors used by teachers from diverse cultural and educational backgrounds and conduct longitudinal studies to explore how teacher perceptions evolve as AI becomes more prevalent in education.

References

- Akbaba, S. A. (2002). Okul yöneticilerinin teknolojiye karşı tutumlarının incelenmesi [Examining school administrators' attitudes towards technology]. *Çağdaş Eğitim Dergisi*, 27, 8-14. Retrieved from <https://www.researchgate.net/publication/286284931> Okul yöneticilerinin teknolojiye karşı tutumlarının incelenmesi
- Akçin, M. (2023). *Sınıf Öğretmenlerinin Kodlama ve Robotik Algılarının Metafor Analizi Yöntemi İle Belirlenmesi [Determining Classroom Teachers' Coding and Robotics Perceptions Using Metaphor Analysis Method] (Thesis number: 776105)* [Master Thesis, Gazi University]. Turkish Council of Higher Education Thesis Center.
- Anderson, R. E., & Dexter, S. (2005). School technology leadership: An empirical investigation of prevalence and effect. *Educational Administration Quarterly*, 41, 49-82. <https://doi.org/10.1177/0013161X04269517>
- Arslan, K. (2020). Eğitimde Yapay Zeka ve Uygulamaları [Artificial Intelligence and Applications in Education]. *Batı Anadolu Eğitim Bilimleri Dergisi*, 11(1), 71-88. Retrieved from <https://dergipark.org.tr/en/pub/baebd/issue/55426/690058>
- Arslan, M., & Bayrakçı, M. (2006). Metaforik Düşünme ve Öğrenme Yaklaşımının Eğitim-Öğretim Açısından İncelenmesi [Examination of Metaphorical Thinking and Learning Approach in Terms of Education]. *Millî Eğitim Dergisi*, 171, 100-108. Retrieved from https://dhgm.meb.gov.tr/yayimlar/dergiler/milli_egitim_dergisi/171/171/8.pdf

- Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence*, 3, 100099. <https://doi.org/10.1016/j.caeai.2022.100099>
- Aydın, S., Duman, E., Bertiz, Y., & Birişçi, S. (2022). Investigation of the effects of computer-aided animations on conceptual understanding through metaphors: An example of artificial intelligence. *Journal of Educational Technology & Online Learning*, 5(4), 1140-1159. <https://doi.org/10.31681/jetol.1151460>
- Bearman, M., Ryan, J., & Ajjawi, R. (2023). Discourses of artificial intelligence in higher education: A critical literature review. *Higher Education*, 86(2), 369-385. <https://doi.org/10.1007/s10734-022-00937-2>
- Becker, S. A., Brown, M., Dahlstrom, E., Davis, A., DePaul, K., Diaz, V., & Pomerantz, J. (2018). *Horizon report 2018 higher education edition brought to you by EDUCAUSE*. Retrieved from <https://www.learntechlib.org/p/184633/>
- Bozkurt, A. (2020). Koronavirüs (Covid-19) Pandemisi Sırasında İlköğretim Öğrencilerinin Uzaktan Eğitime Yönelik İmge ve Algıları: Bir Metafor Analizi [Primary School Students' Images and Perceptions of Distance Education During the Pandemic: A Metaphor Analysis]. *Uşak Üniversitesi Eğitim Araştırmaları Dergisi*, 6(2), 1-23. <https://doi.org/10.29065/usakead.777652>
- Chiu, T. K. F., & Chai, C. (2020). Sustainable Curriculum Planning for Artificial Intelligence Education: A Self-Determination Theory Perspective. *Sustainability*, 12(14), 5568. <https://doi.org/10.3390/su12145568>
- Cukurova, M., Luckin, R., & Kent, C. (2020). Impact of an Artificial Intelligence Research Frame on the Perceived Credibility of Educational Research Evidence. *International Journal of Artificial Intelligence in Education*, 30(2), 205-235. <https://doi.org/10.1007/s40593-019-00188-w>
- Dai, Y., Chai, C.-S., Lin, P.-Y., Jong, M. S.-Y., Guo, Y., & Qin, J. (2020). Promoting Students' Well-Being by Developing Their Readiness for the Artificial Intelligence Age. *Sustainability*, 12(16), 6597. <https://doi.org/10.3390/su12166597>
- Demir, K., & Güraksin, G. E. (2022). Determining middle school students' perceptions of the concept of artificial intelligence: A metaphor analysis. *Participatory Educational Research*, 9(2), 297-312. <https://doi.org/10.17275/per.22.41.9.2>
- Ekici, G. (2016). Öğretmen Adaylarının "Bilgisayar" Kavramına İlişkin Metaforik Algıları [Metaphorical Perceptions of Teacher Candidates Regarding the Concept of "Computer"]. *Gaziantep University Journal of Social Sciences*, 15(24216), 755-781. <https://doi.org/10.21547/jss.256704>
- Er, M. B., Balıkçı, H. C., Alpsülün, M., Bozdağ, Z., Yıldız, A., Tezcan, A., & Yildirim, N. T. (2023). Yapay Zeka Uyumlu Algoritmalarla Öğrencilerin LGS Puanı Tahmini ve Modellenmesi. *Necmettin Erbakan Üniversitesi Ereğli Eğitim Fakültesi Dergisi*, 5(2), 377-402. <https://doi.org/10.51119/ereegf.2023.61>
- Flanagan, L., & Jacobsen, M. (2003). Technology leadership for the twenty-first century principal. *Journal of Educational Administration*, 41(2), 124-142. <https://doi.org/10.1108/09578230310464648>
- Güneş, A., & Fırat, M. (2016). Açık ve uzaktan öğrenmede metafor analizi araştırmaları [Metaphor analysis research in open and distance learning]. *Açıköğretim Uygulamaları ve Araştırmaları Dergisi*, 2(3), 115-129. Retrieved from <https://dergipark.org.tr/en/pub/auad/issue/34059/377003>
- Hacıfazlıoğlu, Ö., Karadeniz, Ş., & Dalgıç, G. (2011). Okul yöneticilerinin teknoloji liderliğine ilişkin algıları: Metafor analizi örneği [School administrators' perceptions of technology leadership: An example of metaphor analysis]. *Eğitim Bilimleri Araştırmaları Dergisi*, 1(1), 97-121. Retrieved from <https://dergipark.org.tr/en/download/article-file/696382>
- Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*.

- Kalaycı, S. (2018). İlkokul öğrencilerinin “bilim” ve “fen bilimleri dersi” kavramlarına yönelik algılarının metafor yoluyla belirlenmesi [Determining primary school students' perceptions of the concepts of "science" and "science course" through metaphor]. *Uluslararası Sosyal ve Eğitim Bilimleri Dergisi*, 5(9), 1-21. <https://doi.org/10.20860/ijoses.351611>
- Kaleli Yılmaz, G., & Güven, B. (2015). Determining the Teacher Candidates' Perceptions on Distance Education by Metaphors. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 6(2), 299. <https://doi.org/10.16949/turcomat.75936>
- Kasepalu, R., Prieto, L. P., Ley, T., & Chejara, P. (2022). Teacher Artificial Intelligence-Supported Pedagogical Actions in Collaborative Learning Coregulation: A Wizard-of-Oz Study. *Frontiers in Education*, 7, 736194. <https://doi.org/10.3389/educ.2022.736194>
- Kılıç, S. (2015). Kappa testi [Kappa test]. *Journal of mood disorders*, 5(3), 142-144. <https://doi.org/10.5455/jmood.20150920115439>
- Koç Akran, S., & Karakaş, G. (2023). Öğretmen Adaylarının Z Kuşağı Kavramına İlişkin Algılarının Belirlenmesi Bir Metaforik Analiz Çalışması [Determining the Perceptions of Teacher Candidates on the Concept of Generation Z: A Metaphorical Analysis Study]. *Anadolu Eğitim Liderliği ve Öğretim Dergisi*, 11(1), 103-129. Retrieved from <https://dergipark.org.tr/en/pub/ajeli/issue/78579/1270363>
- Kösterelioğlu, M. A. (2014). Öğretmen adaylarının okul yöneticisi kavramına ilişkin metaforik algıları [Metaphorical perceptions of teacher candidates regarding the concept of school administrator]. *Zeitschrift für die Welt der Türken*, 6(3), 115-133. Retrieved from <https://dieweltdertuerken.org/index.php/ZfWT/article/view/570>
- Lakoff, G., & Johnson, M. (1980). *Metaphors we live by*. University of Chicago, Chicago, IL. http://www.cc.gatech.edu/classes/AY2013/cs7601_spring/papers/Lakoff_Johnson.pdf
- Lin, H. (2022). Influences of Artificial Intelligence in Education on Teaching Effectiveness: The Mediating Effect of Teachers' Perceptions of Educational Technology. *International Journal of Emerging Technologies in Learning (ijET)*, 17(24), 144-156. <https://doi.org/10.3991/ijet.v17i24.36037>
- Lindh, M., & Nolin, J. M. (2017). GAFAspeaks: Metaphors in the promotion of cloud technology. *Journal of Documentation*, 73(1), 160-180. <https://doi.org/10.1108/JD-03-2016-0039>
- Milli Eğitim Bakanlığı. (2023, November 30). Ortaokullarda “Yapay Zekâ Uygulamaları” Dersinin Müfredatı Hazırlandı [The Curriculum of the "Artificial Intelligence Applications" Course in Secondary Schools was Prepared.]. Retrieved from <https://www.meb.gov.tr/ortaokullarda-yapay-zek-uygulamalari-dersinin-mufredati-hazirlandi/haber/31761/tr>
- Morgan, G. (1980). Paradigms, metaphors and puzzle solving in organization theory. *Administrative Science Quarterly*, 25(4), 605-622. <https://doi.org/10.2307/2392283>
- Moustakas, C. (1994). *Phenomenological research methods*. Sage publications.
- Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI -powered educational technology and a professional development program to improve it. *British Journal of Educational Technology*, 53(4), 914-931. <https://doi.org/10.1111/bjet.13232>
- Pelletier, K., McCormack, M., Muscanell, N., Reeves, J., Robert, J., & Arbino, N. (2024). *2024 EDUCAUSE Horizon Report: Teaching and Learning Edition*.
- Sabahat, Ö., Alper, U., Gören, S. Ç., Kaymak, M. N., & Göregen, F. (2023). Öğrenci, Öğretmen ve Yöneticilerin Covid-19 Salgını ile Değişen Metaforik Okul Algısı [Metaphorical School Perception of Students, Teachers and Administrators Changing with the Covid-19 Pandemic]. *Başkent University Journal of Education*, 10(1), 97-112. Retrieved from <https://buje.baskent.edu.tr/index.php/buje/article/view/524>

- Saban, A. (2004). Giriş düzeyindeki sınıf öğretmeni adaylarının “öğretmen” kavramına ilişkin ileri sürdükleri metaforlar [Metaphors put forward by entry-level classroom teacher candidates regarding the concept of "teacher"]. *Türk eğitim bilimleri dergisi*, 2(2), 131-155. Retrieved from <https://dergipark.org.tr/en/pub/tebd/issue/26128/275216>
- Saban, A. (2008). İlköğretim I. Kademe Öğretmen ve Öğrencilerinin Bilgi Kavramına İlişkin Sahip Oldukları Zihinsel İmgeler [Mental Images of Primary School First Level Teachers and Students Regarding the Concept of Knowledge]. *İlköğretim Online*, 7(2), 421-455. Retrieved from <https://dergipark.org.tr/en/pub/ilkonline/issue/8601/107119>
- Saban, A. (2009). Öğretmen adaylarının öğrenci kavramına ilişkin sahip oldukları zihinsel imgeler [Mental images that teacher candidates have regarding the concept of student]. *Türk eğitim bilimleri dergisi*, 7(2), 281-326. Retrieved from <https://dergipark.org.tr/en/download/article-file/256272>
- Saçan, S., Tozduman Yaralı, K., & Kavruk, S. Z. (2022). Çocukların “Yapay Zeka” Kavramına İlişkin Metaforik Algılarının İncelenmesi [Examining Children's Metaphorical Perceptions of the Concept of "Artificial Intelligence"]. *Mehmet Akif Ersoy Üniversitesi Eğitim Fakültesi Dergisi*, 64, 274-296. <https://doi.org/10.21764/maeuefd.1074024>
- Wildman, T., & Niles, J. (1987). Reflective teachers: Tensions between abstractions and realities. *Journal of Teacher Education*, 3, 25-31. <https://doi.org/10.1177/002248718703800405>
- Yıldırım, A., & Şimşek, H. (2016). *Sosyal Bilimlerde Nitel Araştırma Yöntemleri [Qualitative research methods in the social sciences]* (10. ed). Seçkin Yayınevi, Ankara.
- Zhao, L., Wu, X., & Luo, H. (2022). Developing AI Literacy for Primary and Middle School Teachers in China: Based on a Structural Equation Modeling Analysis. *Sustainability*, 14(21), 14549. <https://doi.org/10.3390/su142114549>

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Present and Future of Artificial Intelligence: A Case Study on Prospective Teachers

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Abstract: This study investigates prospective teachers' perspectives on the present status of artificial intelligence (AI) and their predictions regarding its future development. The study utilized a case study approach to select a group of 64 prospective teachers from the faculty of education at a state university in Türkiye. The study participants comprised 34 female and 30 male prospective teachers. The researchers employed a purposive sampling technique, specifically the criterion sampling approach, to select the prospective teachers included in the study. The researchers collected data for the study using the "AI Perception Interview Form" and the "AI Future Foresight Determination Form," and then analyzed the data using descriptive and content analysis techniques. The results showed that prospective teachers obtained information about AI primarily from social media, internet/news websites, and applications. Analyzing the definitions and explanations provided by the prospective teachers revealed that they particularly emphasized the uploading of human intelligence to computer systems, the acquisition of human-like abilities by machines, and the ability of AI to learn independently. Additionally, prospective teachers identified health, education, accounting, and finance as domains with significant potential for the advancement of AI. In education, the initial applications prospective teachers thought AI could be used for included determining students' mental states, assessing student levels, and providing personalized content. The data obtained from the study indicate that prospective teachers produced both utopian and dystopian content regarding the future of AI. This production of varied content reveals that prospective teachers have diverse perspectives on the future of AI.

Keywords: Prospective Teachers, Artificial Intelligence, AI Perceptions, Education, AI Future Predictions

1. Introduction

Artificial Intelligence (AI) is a computer technology that mimics human cognition and can work faster and more effectively than human intelligence in some areas. Gondal (2018) states that AI can perceive, interpret, learn, and infer the essential characteristics of human intelligence. Human intelligence continues to surpass AI at present. However, it is seen that AI works faster and more effectively than the human brain in solving complex tasks and under rapidly changing conditions (Teng, 2019). According to the definition provided by Obschonka and Audretsch (2020), AI can be summarized as the ability to solve complex problems and adapt to changing conditions using human intelligence's reasoning and prediction abilities. Although AI is a term coined by McCarthy in 1956 (Ertel, 2011), there has been a rapid increase in the number of studies in this field. Singh et al. (2013) stated that AI has various skills, such as performing in specialized areas, problem-solving, natural language communication, and object recognition. In this context, AI functions as a computer brain and is considered a branch of science representing studies in this field. Since 1956, AI has been developing rapidly, and this development process will continue rapidly in the coming years in line with technological advances. According to Boucher (2019), the three prominent concepts of AI are artificial general intelligence that is not limited to specific fields, artificial superintelligence that exceeds human intelligence, and AI that becomes autonomous. These concepts allow for predicting the future development of cognitive abilities where AI can surpass human intelligence. AI is used in many areas, including communication, digitalization of business and transactions, rapid access to information, health, and security (Komalavalli et al., 2020).

AI influences our lives through its functionalities, including perception, self-learning, and decision-making. In the near future, it is anticipated that AI will further enhance human existence and assume a more prominent role in daily affairs. However, these developments also bring along some concerns. In particular, concerns about the privacy and use of data collected as AI occurs in all areas of life are increasing (Oliveira et al., 2020). There are also concerns about the uncontrolled use of AI, increased unemployment, and increased war casualties (Fast & Horvitz, 2017). In particular, the potential of AI to replace humans in the labor market is one of the most debated issues today.

Although it is not possible to make a definite prediction about the future AI, it is possible to make predictions by looking at the realization of predictions made in the past. For example, in 1957, Simon predicted that computers would become chess champions within ten years. Similarly, in 1973, Oscar Firschein and SRI engineers made predictions about the release dates of certain products in consultation with AI experts. They offered the possibility of changing these predictions with the Delphi method (Firschein et al., 1973). One of the most essential points where advanced technology differs from traditional technologies is that a more efficient production process becomes possible by using fewer production inputs such as labor, natural resources, and energy. A significant portion of the investments made, especially in developed countries, are realized as investments involving advanced technology, and this trend is expected to continue in the future (Taşkın & Adalı, 2004, p. 140). This shows that highly critical technology such as AI will become more widespread and record a significant development.

AI studies have made significant progress in the last two decades. With the applications of AI, situations and events considered very difficult in the history of humanity can be faced today without difficulty (Acar, 2020). Looking at the applications of AI in human sciences, there is a general belief that AI only enables the control of machines or robots. However, unlike this belief, with the increase in social media platforms such as Instagram, Facebook, and Twitter, which turn people's behavior and the movements of society into data, changes occur in the methods and processes of individuals communicating and interacting, acquiring and disseminating information. Consequently, there is a discernible rise in the efficacy of AI observed in studies conducted within fields categorized as human sciences and social sciences. It is possible to predict who will reshare a post shared on Twitter based on author, text and content-based features (Xu & Yang, 2012, p. 48). It is possible to diversify applications similar to this example. It seems possible to encounter the information provided to individuals by tracking the traces on websites in every field. An AI application that takes people to a desired address from the most convenient route, such as offering various individual suggestions with the information obtained from previous purchases in the virtual environment, makes people's lives more accessible in terms of spending less time and effort (Sariel, 2017, p. 22). Access to information becomes easier through AI, and sharing and accessing existing materials, especially in educational applications, with this system becomes much more accessible. However, this is only possible for individuals who can access systems using AI.

Human-AI interaction is a solution or collaboration that can help people worldwide. Therefore, current technologies can inspire people to use AI for education and training. It can motivate students and teachers to be more involved in learning and teaching. The Encyclopedia of Science, Technology, and Ethics (Kelley & Knowles, 2016) refers to AI as "the hybridization of man and machine". In addition, AI refers to semi-robotic human beings who aim to make the human body more qualified and biologically superior (van Hooijdonk, 2017). Complex computing systems using machine learning algorithms and AI can help individuals with different abilities. They are also involved in some human-like processes and can perform complex tasks in teaching and learning. This interaction between humans and machines is a breakthrough in helping humans acquire knowledge and memorize.

Studies in AI play a significant role in developing intelligent systems that produce solutions to a specific problem by modeling the most intelligent beings (Coppin, 2004). AI is a field of study based on human intelligence, and one can imitate it through computers and generate products in different areas of daily life. With AI, it is possible to develop computer systems that artificially produce intelligent thoughts and behaviors of beings in nature (Ayдын, 2017; Balaban & Kartal, 2015). In addition, AI technologies have

come to the forefront in many areas of life with the ability of artificial neural networks, which are included in the concept of AI, to produce solutions to events that have never been encountered before by learning from the available data (Atasoy, 2012, p. 39; Yilmaz, 2012, p. 34). These technologies, which are included in our daily lives in almost every field, such as health, security, software, and communication, are also used in the field of educational technology, as stated in the 2018 higher education version of the NMC (New Media Consortium) Horizon Report (Becker et al., 2018). In this direction, many countries, such as Russia and China, have gradually started integrating AI technologies into education (Nabiyev & Erümit, 2020). In Türkiye, under the coordination of the Digital Transformation Office, which serves under the Presidency of the Republic of Türkiye, various projects are being prepared regarding AI in institutions/organizations serving in the field of education, such as the Ministry of National Education, YÖK, and universities. Efforts are being made to put these projects into practice. These projects cover digital classrooms, lifelong learning approaches, talent hunting for qualified human resources, and new education models (Tamer & Övgün, 2020). As one of the first applications in this context, MoNE launched the EBA Assistant application to instantly meet the needs of students and their parents enrolled in distance education courses. This situation again shows the need for AI-based online education applications in special situations such as the COVID-19 pandemic. In contemporary times, unique circumstances such as the pandemic have necessitated the implementation of distance education for educational and training processes, leading to a widespread transition to digital learning environments within this domain. The technical revolution in this field (Nabiyev & Erümit, 2020), consisting of internet networks with high connection speed, AI, big data, and cloud services, is essential in transitioning to the digital environment.

Many countries are actively pursuing the integration of AI technologies into education. The objective of these endeavors is not to supplant teachers in the educational sphere but rather to liberate them from mundane tasks, enhance the professionalism, engagement, and enjoyment of lessons, curate the most suitable teaching materials for particular student demographics, and foster lasting learning experiences by simplifying the learning process (Nabiyev & Erümit, 2020). In addition, studies on integrating AI technologies into the educational process and creating online learning environments with these technologies can be used to identify student dynamics based on student's learning experiences and to support students' learning processes within the framework of these variables. In this direction, AI technologies are suggested as an assistant for the teacher in the learning process. For the teacher to benefit from AI technologies while organizing the teaching process, he/she should have knowledge and awareness about these technologies. In recent literature, there has been an emergence of studies investigating the utilization of AI within higher education (Khare et al., 2018; Popenici & Kerr, 2017; Taşçı & Çelebi, 2020). For instance, Taşçı and Çelebi (2020) specifically examined the implementation of AI technologies in higher education settings. They discussed how these institutions can prepare for the future with AI technologies. In another study, Khare et al. (2018) researched the adoption of AI technologies in education, considering technological, social, political, economic, cultural, and ethical variables. Popenici and Kerr (2017) investigated the impact of AI technologies in higher education, focusing on their effects on students' learning styles, teaching processes within educational institutions, and the evolution of these processes.

The rapid development of technology is intensifying the influence of AI and automation across nearly every facet of work and daily life. Consequently, the field of education is undergoing an inevitable transformation amid this period of change. The development of AI plays a role in supporting and shaping educational processes. However, in this process, it is critical that prospective teachers, who will raise the future generations, have knowledge about AI and can use this technology effectively in education. Considering that teachers are individuals who directly impact the future of society, the adaptation of prospective teachers to current technology as the cornerstones of the education system and their ability to use technology effectively play a critical role in shaping students' future. AI, popular among current technologies, enables learning-teaching environments to become more effective, better understand student needs, and create personalized learning experiences. AI systems can analyze student data to personalize learning experiences based on each student's strengths and weaknesses, making learning

more efficient and tailored. Additionally, AI automates the assessment of exams and assignments through natural language processing (NLP), reducing the workload of teachers and providing quicker, more consistent evaluations. AI-powered virtual assistants offer 24/7 support to students, answering questions and aiding in their learning processes, thus fostering independent learning skills. Furthermore, AI utilizes big data analytics to monitor and analyze learning behaviors, helping educators and administrators track student progress and optimize educational strategies.

In classroom management and lesson planning, AI assists teachers by analyzing student participation and performance, offering insights and recommendations to enhance teaching methods and classroom dynamics. In STEM education, AI provides innovative tools and applications, such as simulations and modeling, allowing students to grasp complex scientific concepts more effectively. Moreover, AI can assess and enhance students' emotional intelligence and social skills by analyzing their emotional states and social interactions, providing feedback to improve their social engagement. These advancements underline the importance of prospective teachers being well-versed in AI technologies to effectively integrate them into their teaching practices and better prepare students for the future.

Examining prospective teachers' interpretations, knowledge sources, and areas of growth concerning AI is crucial for the future of the education system and for preparing them to navigate this transformation. Such investigations can aid prospective teachers in enhancing their proficiency in technology-related domains and formulate strategies for efficiently integrating AI in education. Additionally, it can bolster the competitiveness of prospective teachers in the job market by ensuring they are better prepared for their post-graduation careers. This, in turn, contributes to economic and social advancement at both individual and societal levels. Empowering prospective teachers with knowledge and competencies related to AI will fortify the prospects of students by equipping them to leverage technology effectively in their educational journeys. This endeavor is pivotal in fostering a more sustainable future for society. Therefore, the exploration of AI education holds paramount significance, and endeavors in this realm should be endorsed and incentivized.

It is widely believed that prospective teachers, who will play a crucial role in shaping the future of education and training, should possess a comprehensive understanding of the concept of AI and be cognizant of its potential applications. It is essential to reveal prospective teachers' awareness of AI and to determine their predictions about how it will be used in education. By determining the current situation of AI in terms of prospective teachers and investigating the predictions for the future of AI, it can be ensured to determine the awareness of AI as well as to reveal the predictions about the development process of AI. Understanding prospective teachers' awareness of AI (AI) and their predictions regarding its future applications in education is paramount. As educators-to-be, their perceptions of AI will significantly influence how they integrate technological advancements into their teaching practices and shape the learning experiences of future generations. By examining the current landscape of AI awareness among prospective teachers and delving into their forecasts for its educational utilization, we aim not only to gauge their comprehension of AI but also to uncover insights into the trajectory of AI development within educational contexts. In essence, this investigation seeks to bridge the gap between theoretical understanding and practical application, shedding light on the evolving role of AI in education and empowering prospective teachers to harness its potential effectively.

This study investigated the perspectives of prospective teachers regarding the concept of AI and their forecasts regarding its future implications. Within the framework of this purpose, the sub-objectives of the study are as follows:

1. What are prospective teachers' sources of information about AI?
2. What are prospective teachers' definitions/explanations regarding AI?
3. What are prospective teachers' thoughts about the development of AI in the future?

4. What are prospective teachers' thoughts about the use of AI in education?

5. What are prospective teachers' predictions of AI?

2. Method

2.1. Research model

In the study conducted to determine prospective teachers' awareness of the current situation of AI and their predictions of AI, the case study method was used. The case study is a research method that describes a current phenomenon or existing situation within its conditions (Cohen et al., 2007; Yin, 2009). In addition, a case study is a methodological approach that involves an in-depth examination of a limited system using multiple data collection to collect systematic information about how that system functions and works (Chmiliar, 2010). Merriam (2013) defines a case study as an exhaustive depiction and analysis of a constrained system. Conversely, according to Creswell (2007), a case study constitutes a qualitative research methodology wherein the researcher scrutinizes one or more time-bound situations extensively, utilizing various data collection instruments (such as observations, interviews, audiovisual materials, documents, and reports) involving multiple sources. Through this process, the researcher elucidates situations and themes pertinent to the context under investigation. In light of the aim of this study to systematically gather data elucidating prospective teachers' perspectives on the current landscape of AI and their prognostications regarding its future trajectory, the case study method is deemed appropriate for the nature of the inquiry.

2.2. Participants

The study group, which was conducted using the case study method, consisted of 64 prospective teachers studying at the faculty of education of a university in the Marmara Region of Türkiye in the 2023-2024 academic year. Of the prospective teachers in the study, 34 were female, and 30 were male. The participants included in the scope of the study are indicated with codes (P-1, P-2...) according to the order. The "criterion sampling" approach, one of the purposeful sampling methods, was preferred in determining the prospective teachers who took part in the research study. The basic understanding of the criterion sampling method is to study all situations that meet a set of criteria determined by the researcher or prepared in advance (Yıldırım & Şimşek, 2011). In studies where criterion sampling is preferred, observation units can be formed of people, events, or situations with certain qualities. In this case, the units corresponding to the criteria determined for the sample are included in the sample (Büyüköztürk et al., 2014). In the selection of prospective teachers to be included in this research, their qualifications were taken into consideration and the basic criteria were that the candidates had taken courses on AI or participated in a training program on AI.

2.3. Data collection tools

As a data collection tool in the study, the researcher developed the "AI Perception Interview Form" and the "AI Future Foresight Determination Form" in order to determine what the prospective teachers' sources of information about AI are, how they define AI, what their views on the development of AI are, what their thoughts about its use in education are, and what their predictions about of AI are. In the preparation phase of the forms, a literature review was conducted, and then the "AI Perception Interview Form" was created by utilizing the Çam et al. (2021) study. This form includes four questions regarding prospective teachers' definitions of AI, sources of information on AI, and their views on the development of AI and its use in education. The second data collection tool of the study, the "AI Future Foresight Assessment Form" was created based on the study conducted by Uymaz (2023) and was used to determine prospective teachers' predictions of AI. Within this form, prospective teachers are also requested to express their predictions about the future of AI either through drawing a picture or writing a story. The forms prepared by the researcher underwent scrutiny by two field experts: one specializing in measurement and evaluation and the other in linguistics. Following this review, the forms were refined and finalized based on the feedback provided by the experts.

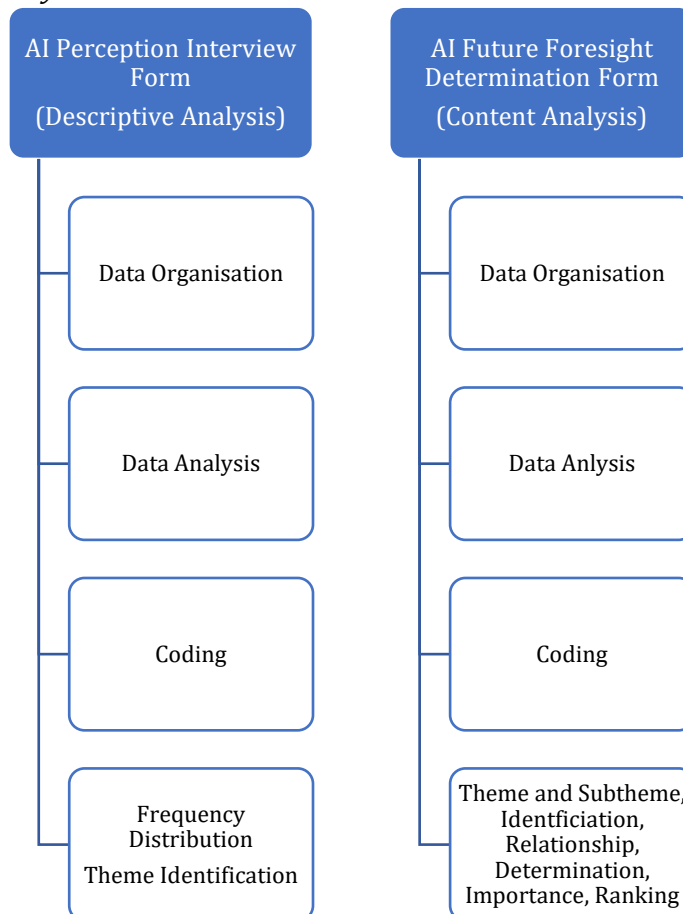
2.4. Data analysis

The data for this study were collected using the document analysis method. Document analysis is a qualitative research method that involves the systematic examination and interpretation of existing documents (Bowen, 2009). The data collected through the "AI Perception Interview Form" and the "AI Foresight Assessment Form" which were used to determine prospective teachers' views on AI, were analyzed using the descriptive analysis and content analysis methods (Figure 1).

The data obtained with the "AI Perception Interview Form" was analyzed with the descriptive analysis method. Descriptive analysis, a qualitative data analysis type, involves summarizing and interpreting the data obtained through various data collection techniques according to predetermined themes. The data collected with "AI Foresight Assessment Form" was analyzed using the content analysis method. Content analysis is a research technique for making replicable and valid inferences from data to their context. It involves systematic coding and categorizing of data to identify patterns, themes, and meanings. The primary purpose of this type of analysis is to present the findings to the reader in a summarized and interpreted form (Yıldırım & Şimşek, 2011). In descriptive analysis, a data analysis framework is established either based on the research problems or the conceptual framework of the study. This framework outlines how the data will be structured and presented. Subsequently, the acquired data are organized, and the findings are delineated. In the final stage, the findings are elucidated, linked, and given significance (Büyüköztürk et al., 2014). In this study, the data collected from prospective teachers were analyzed in alignment with the study's objectives and research questions. In order to increase the comprehensibility of the data obtained with the descriptive analysis method, examples from student responses were included in the findings section. The findings obtained within the framework of these examples are presented by establishing and interpreting relationships with studies on similar topics.

Figure 1

Process of Data Analysis



2.5. Validity and reliability

To ensure the validity of the study, various methods were employed, including researcher diversification, maintaining a prolonged study duration, and soliciting input from three experts both during the development of data collection tools and the analysis phase. Additionally, detailed descriptions and purposive sampling were implemented to enhance the external validity (transferability) of the study findings. Accordingly, documents were analyzed without alteration during the data collection phase, and academic literature pertaining to the study topic was thoroughly examined. The data derived from these analyses were comprehensively described to promote external validity and consistency of the study (Yıldırım & Şimşek, 2011).

Expert opinions were sought from two researchers to assess the reliability of the categories and subcategories developed throughout the study. Subsequently, the codes and themes were cross-referenced with the categories independently generated by two researchers through a separate content analysis. The comparative reliability of the coders was calculated using Miles and Huberman's (1994) formula [$\text{Consensus} / (\text{Consensus} + \text{Dissensus}) \times 100$], resulting in a reliability score of 90.3%. It is worth noting that a reliability score exceeding 70% is generally deemed satisfactory for research purposes (Miles & Huberman, 1994).

3. Findings

For the first sub-objective of the study, which focuses on "What are the sources of information that prospective teachers used in order to acquire information regarding AI?" the responses provided by the prospective teachers are presented in Table 1. In this analysis, the suitability of features was promptly observed by prospective teachers due to the diversity of sources noted in the total number of responses.

Table 1

Distribution of Information Sources Used by Prospective Teachers on AI

Information Resources	f
Social Media	23
Web/News Web Sites	20
AI Applications	15
Research Article	8
Books	6
Friends	6
Training Programs on AI	5
YouTube	5
Movies/Series	4
Magazines	3
Chatbots	2
Secondary Schools	1
Television	1
Total	93

When the data in Table 1 regarding the sources of information used by prospective teachers regarding AI are examined, it is seen that 23 prospective teachers mentioned social media, 20 prospective teachers mentioned internet/news sites, and 15 prospective teachers mentioned AI applications. In addition, prospective teachers' sources of information about AI include books, friends, and training programs on AI.

Within the scope of the second sub-objective of the study, "What are the prospective teachers' definitions/explanations regarding AI?" Regarding the study question, prospective teachers define AI as having computer systems perform the activities that human intelligence can perform, enabling machines to perform features such as acquiring information, thinking and perceiving with high performance, computers performing problem-solving tasks, simulation of programmed human intelligence, systems that imitate human intelligence, and the ability to perform tasks such as obtaining information, thinking and perceiving with high performance. A set of systems that try to give the appropriate answer, programs that enable the work, tasks and activities of the information loaded into the machines to be carried out quickly, the development of coded systems with machine learning, programmed algorithm technology to display human-like thinking abilities, stimulating learning and creativity abilities in the computer environment, people. It has been determined that digital intelligence is defined as the computer's ability to perform tasks such as learning, problem-solving, language understanding, image recognition, and decision-making. Regarding their definition of AI, P-25 stated that *"AI is a field of technology and science that conducts research to transfer the activities that human intelligence can perform to computer systems."* P-24 defined it as *"the ability of machines to perform features of natural intelligence such as acquiring information, thinking and perceiving with a high performance."* P-6 *"A computer or robot learns like a human and performs tasks such as problem-solving"*, P-8 *"AI is the simulation of human intelligence programmed to think, respond and learn like humans."*, P-63 *"AI is the simplest way to perform certain tasks."* *"AI is a set of systems that give the most appropriate response to the inputs given and try to update themselves with the information they collect and give better results"*, P-46 *"They are systems that imitate human intelligence to fulfill their needs and improve themselves by repeating the information they collect."* *Programs that enable the information loaded into machines to perform various jobs, tasks, and activities more quickly and practically*, P-60 *"AI coded systems gradually develop with machine learning and become AI"*, P-53 *"AI performs certain tasks."* *"A technology that includes programmed algorithms to bring intelligence or display human-like thinking abilities"*, P-62 *"AI is the imitation of natural intelligence as computers or devices with similar processing power and reviving the learning and creativity abilities of humans in a computer environment"*, P-10 They defined it as *"AI is digital intelligence designed by humans"*, and P-45 is *"AI simulates human-like intelligence features such as learning, problem solving, perception, understanding, language comprehension, and decision making."*

Regarding the third sub-objective of the study, "What are the thoughts of prospective teachers about the development of AI in the future?" The answers prospective teachers gave to the study question are shown in Table 2.

Table 2*Distribution of Prospective Teachers' Responses Regarding the Areas Where AI Can Develop*

Development Area of AI	f	Development Area of AI	f	Development Area of AI	f
Healthy system	25	Library Services	2	R&D Studies	1
Education	24	Technology	2	Energy	1
Accounting and Finance	7	Software	2	Automation	1
Visual Arts	6	Mathematics	2	Cyber Safety	1
Automotive	5	Law	2	Informatics	1
Language Learning and Translation	5	Robotics	2	Engineering	1
Defense Industry	5	Psychology	2	Communication	1
Agriculture	4	Games	1	Business Administration	1
Production	4	Trading	1	Risk Assessment and Prevention	1
Transportation and Logistics	4	Service	1		
Security	3	Counseling	1		
Total					119

According to Table 2, prospective teachers who participated in the study, listed health comes first when it comes to areas where AI can develop. Followed by education, accounting and finance, visual arts, and automotive.

Regarding the fourth sub-objective of the study, "What are prospective teachers' thoughts about the use of AI in education?" The answers given by the prospective teachers to the study question are shown in Table 3.

Table 3*Distribution of AI-Supported Applications That Can Be Used in Education According to Prospective Teachers*

Education Application	f	Education Application	f	Education Application	f
Determining students' mental states	5	Learning with fun	1	Recording information provided by the teacher	1
Identifying the student's level and providing personalized content	4	Learning with VR glasses	1	Robot assistant	1
Reinforcing the information learned	4	Developing activities based on curricula	1	Interactive book	1
Identifying missing learning	2	Determining readiness and preliminary information	1	Applications for special children	1
Evaluation of learning	2	Application integrated into the curriculum	1	Moral and ethical values	1
Survey-oriented application	2	Preparing activities according to students' learning styles	1	Create animation	1
Language development	2	Preparing a personal plan	1	Trial exam performance evaluation	1
Designing games that suit the student's interests	2	University voice assistant	1	Smart Assistant	1
Personalized progress tracking	2	An application for using Turkish correctly	1	AI coach	1
Hologram application	2	Repository application	1	Games for teaching mathematics	1
Application for visually impaired people	1	Creating visual and audio material	1	Getting to know the student	1
Homework app	1	AI applications that students can develop	1	Consistency between exams	1
AI assistant (introducing human organs)	1	An application that recognizes the student	1	Resolving meaning difficulties	1
Determining the teaching method according to the subject	1	Recycling Applications	1	Emotion Teaching	1
Visualization of novels and stories	1	Tablet notebook	1	Virtual school	1
Language learning application	1	Turkish teaching	1		
Total					64

According to Table 3, prospective teachers identified several primary applications for AI in education. These include determining students' mental states, assessing students' proficiency levels, and delivering personalized content. Additionally, teachers highlighted the importance of AI in reinforcing learned information and identifying gaps in learning.

Within the scope of the study, prospective teachers were asked to reflect on their predictions about what AI might be like in the future by writing a fictional story or drawing. The data evaluated separately as stories and pictures are given in Table 4.

Table 4*Predictions and Distributions of Prospective Teachers Regarding the Future of AI*

Story/Picture	Utopian	Dystopian	Total
Story	34	18	52
Picture	9	3	12
Story and Picture	5	1	6
Total	48	22	70

According to the data obtained from Table 4, the participation level of prospective teachers regarding the future of AI is as follows: 52 participants wrote stories, 12 participants drew pictures, and 6 participants did both. The participants who wrote stories, submitted 34 utopian and 18 dystopian fiction, while among those who drew pictures, 9 focused on utopian and 3 dystopian objects. The ones who both write stories and draw pictures, submitted 5 utopian and 1 dystopian works. According to the data obtained within the scope of the study, a total of 70 data, 48 utopian and 22 dystopian, were determined. The analysis revealed that the prospective teachers who participated in the study tended to articulate more utopian narratives concerning the future of AI than dystopian ones.

P-3, one of the prospective teachers said the following about the future of AI *"Canan opened her eyes, took the chip plugged into the charger and placed it on her shoulder. He had been sick for the last two days, he checked the ideal menu from the phone application connected to the chip on his shoulder to find out what he should eat for dinner. He created the menu he wanted and headed to the kitchen. When he looked at the timer on the counter and saw how many minutes were left until the robot prepared the meal, he headed to the bedroom to put on his clothes. "The phone application that reviewed the weather forecasts listed clothing combinations suitable for the weather."* P-7 wrote the following short story: *"I am lacking energy today. So, he took energy pills. These pills help balance your hormones, give you energy and boost your mood I am too lazy to make decisions, so I asked Robotgpt, which records everything, "What should I do today?" Robotgpt gave me a few tasks. I wore my virtual suit and I simulated these tasks. Then I wanted to try the playroom I just bought to play games. "It is a room that Helps you experience everything in the game, including the smell of the virtual reality environment."* He wrote a story about the future use of AI in daily life. P-14 *"I woke up today with Hüsni yelling at me. He was quite angry that it took me time to wake up. She tidied up the house and prepared my breakfast according to the amount of food I needed for the day and my body's needs. For no reason, I named the technology that controls all electrical appliances in our home as Hüsni. I told him to wake up earlier than usual today because we were going to take a short tour in Spain with my friend. Since Hüsni took care of the travel procedures, all I had to do was teleport to Spain. Since it is enjoyable to do this on Earth, I look forward to the days when I can teleport to nearby planets."* He wrote the following story. P-23 *"I woke up early in the morning. Today was my first day on Venus. Actually, I have lived on many planets before, such as Saturn and Uranus, but I liked this place more. This place is a little farther from the planet Betelgeuse, where I worked. Helps you experience everything in the game, including the smell of the virtual reality environment. My job at a large company is to ensure that AI and societies can be logically placed on planets."* They wrote utopian stories about the future of AI.

P-37, one of the participants who wrote a dystopian story about the future of AI, said: *"2124 gives the impression of a year in which drones are not just observation tools, but the smallest thing we touch can turn into any weapon. The last efforts of humanity to protect the most natural elements of the world are related to both protecting nature and each other."* *"Humanity is probably facing its greatest struggles when working with robots."* He wrote the following story: P-38 *"Life flashed before my eyes: 'Critical adrenaline level, please contact the nearest health center.' While I was experiencing of all these, I heard a familiar*

voice. Ambulance siren. After a while, a small vehicle approached me. I did not have time to react and found myself lying down again. It got dark outside; I was being carried on a stretcher. My vision was going and coming and I could not understand the situation. Then, I heard a loud voice: "Subject RT-2124, test-8 failed as a result of future simulation." P-45 "The people on the streets had different devices inserted in their heads and everyone was acting like they were connected to a machine and receiving commands from a command centre. Meteors were now passing through the sky and not occupying the ground. It was as if humans and robots had changed places, while the humans were emotionless and soulless, the robots were laughing, having fun, getting tired and sleeping." They wrote dystopian stories about the future of AI.

The prospective teachers who participated in the study tried to predict the future of AI with both utopian and dystopian pictures. These pictures and stories have been analyzed and categorized by researchers and domain experts. The pictures drawn by the participants are included in the appendix of the study (Appendix-1). The picture drawn by P-54, one of the prospective teachers tried to reflect that there will be an artificial eye monitoring the living environment, the concept of peace will gain importance The air will be dirty. The picture drawn by P-55, Shows AI-powered robots causing trouble. As a utopian picture, P-56 tried to reflect the new generation's education system with AI. In the picture, he predicted that hologram conservation would achieve teacher-student interaction. P-58 also drawn a picture that corresponds to the fact that many of his daily needs can be met with the help of AI in the future. P-60 tried to reflect his predictions of AI by using objects such as holograms, drone cargo distributors, people living in the virtual world, flying high-speed trains, robot police, and personal flight devices.

4. Discussion, Conclusion, and Recommendations

According to results of the study conducted to examine prospective teachers' opinions and predictions about AI, it was determined that social media was their primary source of information from which prospective teachers obtained their information about AI. In addition to social media, internet/news sites, AI applications, and articles are among the sources used by prospective teachers to obtain information about AI. These results suggest that AI has become an indispensable part of life today and that societies are open to change and transformation. AI applications, which have developed rapidly in the last century, manifest themselves in every aspect of people's daily lives. For example, the spread of AI applications in areas such as phones, online shopping systems, navigation, and online banking transactions enables daily life to be transferred to virtual media. This indicates that AI likely changes individuals' lifestyles, ways of thinking, and perceiving (Özgeldi, 2019). In this context, it seems that social media platforms, especially channels such as Instagram, Twitter, and Facebook, are based on AI and play a decisive role in transferring daily life to virtual media. Therefore, the impact of AI is not only limited to technological infrastructure but also profoundly affects people's social interactions and daily lives. Data suggest that AI's importance and impact will gradually increase and will be used more in daily life (Altun, 2019).

As a result of the analysis regarding the second sub-objective of the study, it was found that prospective teachers were interested in AI, outsourcing the activities that human intelligence can perform to computer systems, enabling machines to perform features such as acquiring information, thinking, and perceiving with high performance, computers performing problem-solving tasks, simulation of programmed human intelligence, systems that imitate human intelligence, a whole of systems that try to give the most appropriate response to given inputs, and machines. Programs that enable the uploaded information to carry out work, tasks, and activities quickly, development of coded systems with machine learning, algorithm technology programmed to display human-like thinking abilities, revitalization of learning and creativity abilities in the computer environment, digital intelligence designed by humans, and computer learning. It was determined that they define/explain the ability to perform tasks such as problem-solving, language understanding, image recognition, and decision making. Prospective teachers mainly focused on uploading human intelligence to computer systems, machines gaining human-like abilities, and the self-learning feature of AI.

In this context, a relationship is observed between the "learnable" aspect of AI emphasized by Luckin (2017) and the conceptual approaches of prospective teachers. In addition, Aydın's (2017) definition of AI as a field of study that imitates human intelligence and develops products in various fields supports the perspective of prospective teachers. Similarly, the ability of AI technologies to imitate the intelligent behavior of creatures in nature and the ability of artificial neural networks to produce innovative solutions by learning from existing data reflect the evolutionary and advanced technological dimensions of prospective teachers' perceptions of AI. In this context, the study results shed essential light on prospective teachers' knowledge and perceptions about AI. It is also stated that AI can imitate intelligent behaviors in nature, and artificial neural networks can produce new solutions by learning from existing data (Aydın, 2017; Balaban & Kartal, 2015; Atasoy, 2012; Yılmaz, 2012). The study results show that prospective teachers' conceptual frameworks regarding AI have developed in line with the technology's current potential and the literature's definitions.

When prospective teachers' opinions about AI are examined in line with the third sub-objective of the study, it seems that AI is expected to affect the developments in the field of health primarily and also be effective in fields such as education, accounting, finance, and visual arts. When these opinions are evaluated according to the literature findings, various AI technologies are presented in different sectors, as stated by Cibaroğlu and Yalçınkaya (2019). However, it is noted that AI technologies in higher education are not extensively adopted, particularly in the realms of education and health services (Bughin et al., 2017). At this point, prospective teachers advocate for further use of AI, especially in education, because of their accurate analysis of the needs in their profession and their understanding of the importance of these technologies to increase the quality of education. As emphasized by Tekgüç and Adalier (2019), teachers should use AI technologies to structure appropriate learning processes by analyzing the individual needs of students. In this context, prospective teachers' perceptions of AI highlight its potential for use in education and offer an essential perspective on changes in future education processes.

When prospective teachers' opinions about AI are examined within the scope of the fourth sub-objective of the study, it is stated that AI has a vast potential for use in education. It is suggested that AI technologies could be used primarily to determine the student's level, provide personalized content, determine mental states, and detect missing knowledge. In addition, prospective teachers emphasize that AI can be used effectively in teaching lessons, carrying out in-class applications, evaluating students individually, and eliminating their deficiencies. These views are also supported in the literature. For example, Sheikh (2020) suggests that AI can be applied in teaching to improve flexible and individualized learning. Similarly, Nabiyevev and Erümit (2020) emphasized that AI technologies can be used in education as teacher assistants, ensure the evaluation of information, and offer personalized learning systems. In this context, it is suggested that learning platforms supported by AI technologies can be an effective tool for students to have individual learning experiences and personalize the learning process. In this regard, Elazab's (2023) view that individual information can be provided for each student with the help of AI systems and that a personalized learning style can be determined so that each student can learn according to his/her ability supports this study result.

Analyses made within the scope of the fifth sub-objective of the study revealed that prospective teachers produced utopia and dystopia content about the future of AI. However, the opinions in the literature stating that the concept of utopia should be understood correctly emphasize that utopia is not only the imagination of a perfect society but also a design that reflects the ideals and ideology of the individual (Ağkaya, 2016). It is suggested that the essence of the utopian idea is shaped by longing for the past and hopes for the future and intersects with the inevitability of progress. In this context, it is stated that the utopias that emerged in the 20th century are reflections of technological and social developments such as digitalization and AI. However, it is suggested that this progress brings with it some fears and dystopias emerge (Özsoy, 2018). It is suggested that the concept of dystopia, as the opposite of utopia, forms a basis of thought in which the interaction of social structure with technology and intellectual designs is discussed with scientific theories. In this context, it can be said that the contents produced by

prospective teachers about the future of AI draw attention to the hopes brought by technological progress, as well as the potential risks and threats it may bring.

The data obtained from the study show that prospective teachers produce both utopian and dystopian content about the future of AI. In the study, most participants preferred to write stories, and these stories primarily focused on utopian content. In particular, some participants describe the potential use of AI in daily life in a utopian way. However, a significant amount of dystopian content is also present. In addition to the story format, participants also drew pictures about the future of AI. The majority of the participants who chose drawing focused on utopian elements regarding the future of AI. In particular, some participants reflect on the positive effects of AI on education and daily life. On the other hand, the drawings also depict the possible dangers of AI. These results suggest that prospective teachers believe that AI will likely affect human life both positively and negatively in the future but the positive effects might be more significant.

The content diversity produced by the prospective teachers participating in the study about the future of AI is remarkable. The higher amount of utopian contents shows that participants generally view AI in a positive light. Nevertheless, there was also a significant amount of dystopian narratives, indicating that prospective teachers are cognizant of the potential risks associated with AI. This diversity of perspectives aligns with the findings of Aǧkaya (2016), which emphasize the importance of considering various viewpoints in discussions concerning the future of AI.

This study was conducted to determine prospective teachers' views on the present and future role of AI (Al-Matari, 2023; Elazab, 2023; Gksel & Bozkurt, 2019; zkaynak, 2020) and emphasizes the increasing importance of AI in education. The most direct result of the application of AI in education is the emergence of an intelligent teaching system. This system forms the basis of computer-assisted teaching and reveals an open human-computer interaction system. In addition, since it is student-centered and computer-based, it supports thinking processes with computer simulations. The field of AI applications in education, now called intelligence teaching systems, is gradually expanding. In this context, prospective teachers' perceptions of AI and its future role are essential in transforming education systems. For this reason, understanding the relationship between AI and education is considered an important issue that should be considered in the preparation process of prospective teachers and the design of educational programs.

The study reveals that prospective teachers mainly learn about AI from digital platforms such as social media. This shows that the role of AI in every aspect of daily life is increasing and that societies are open to change and transformation. When examining the opinions of prospective teachers regarding AI, their attention is primarily directed towards the potential and impacts of AI.

Based on the results of the research, the following recommendations can be made: Studies examining the practical applications of AI technologies in education are of great importance. In particular, more research should be conducted on AI-supported teaching methods, personalized learning experiences, and student assessment systems. Such studies can reveal how to optimize teaching processes by enhancing the effectiveness and efficiency of educational technologies. Additionally, long-term studies should be conducted to understand the effects of AI on education. Such studies can help evaluate the long-term impacts of AI on student achievement, the role of teachers, and educational processes. Finally, studies examining the ethical and social impacts of using AI in education should be increased. This can help us better understand the effects of AI on issues of fairness, equality, and privacy in education and provide guidance for the ethical use of AI technologies.

References

- Acar, O. (2020). *AI: opportunity or threat?* Istanbul, Kriter Publishing.
- Ağkaya, O. (2016). Utopia and dystopia: the influence of politics on literature. *Manisa Celal Bayar University Journal of Social Sciences*, 14(4), 4-23. <https://doi.org/10.18026/cbayarsos.280053>
- Al-Matari, A. S. (2023). AI and the future of teaching and learning. *Conference: Pelita Internasional Conference (PIC)*. <https://doi.org/10.13140/RG.2.2.28132.76160>
- Altun, D. (2019). Virtual reality and AI. In G. Telli (Ed.), *AI and the future* (pp. 139-157). Istanbul, Eastern Publishing House.
- Atasoy, S. (2012). *Modeling performance management in human resources with artificial neural networks and neural fuzzy networks (Thesis number: 322637)* [Master Thesis, Yıldız Technical University]. Turkish Council of Higher Education Thesis Center.
- Aydın, Ş. E. (2017). *AI technology (yesterday, today, tomorrow)* [Master's Semester Project, Çukurova University].
- Balaban, M. E., & Kartal, E. (2015). *Data mining and machine learning*. İstanbul: Caglayan Publishing House.
- Becker, A. S., Brown, M., Dahlstrom, E., Davis, A., DePaul, K., Diaz, V., & Pomerantz, J. (2018). *Horizon report: 2018 Higher Education*. EDUCASE.
- Boucher, P. (2019). How AI works. *EPRS. Panel for the Future of Science and Technology*. Retrieved from [http://www.europarl.europa.eu/RegData/etudes/BRIE/2019/634420/EPRS_BRI\(2019\)6344_20_EN.pdf](http://www.europarl.europa.eu/RegData/etudes/BRIE/2019/634420/EPRS_BRI(2019)6344_20_EN.pdf)
- Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal*, 9(2), 27-40. <https://doi.org/10.3316/QRI0902027>
- Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., & Trench, M. (2017). *AI: The next digital frontier?* McKinsey Global Institute.
- Büyüköztürk, Ş., Kılıç Çakmak, E., Akgün, Ö. E., Karadeniz, Ş., & Demirel, F. (2014). *Research methods in science* (17th Edition). Ankara: Pegem Publishing.
- Chmiliar, L. (2010). Multiple-case designs. In A. J. Mills, G. Eurepas, & E. Wiebe (Eds.), *Encyclopedia of Case Study Research* (pp. 582-583). New York: SAGE Publications.
- Cibaroğlu, M. O., & Yalçinkaya, B. (2019). Big data analytics and AI applications in document and archive management processes. *Information Management*, 2(1), 44-58. <https://doi.org/10.33721/by.570634>
- Cohen, L., Manion, L., & Morrison, K. (2007). *Research methods in education* (5th Edition). Londra: Routledge Falmer.
- Coppin, B. (2004). *AI illuminated*. Massachusetts: Jones and Bartlett Publishers.
- Creswell, J. W. (2007). *Qualitative inquiry & research design: choosing among five approaches* (2nd Edition). New York: SAGE Publications.
- Çam, M. B., Çelik, N. C., Turan Güntepe, E., & Durukan, Ü. G. (2021). Determination of teacher candidates' awareness of AI technologies. *Hatay Mustafa Kemal University Journal of Social Sciences Institute*, 18(48), 263-285. <https://doi.org/10.53444/deubefd.1461048>
- ElAzab M. (2023). The future of teaching and learning in the AI era. *International Journal of Internet Education*, 1(1), 1-8. <https://dx.doi.org/10.21608/ijie.2023.312490>

- Ertel, W. (2011). *Introduction to AI*. Berlin: Springer.
- Fast, E., & Horvitz, E. (2020). Long-term trends in public perception of AI. *Proceedings of the AAAI Conference on AI*, 31(1), 1-7. <https://doi.org/10.1609/aaai.v31i1.10635>
- Firschein, O., Fischler, M. A., Coles, L. S., & Tenenbaum, J. M. (1973). Forecasting and assessing the impact of AI on society. *IJCAI'73: Proceedings of the 3rd International Joint Conference on AI* (pp. 105-120).
- Goksel, N., & Bozkurt, A. (2019). AI in education: current insights and future perspectives. In S. Sisman-Ugur & G. Kurubacak (Eds.), *Handbook of Research on Learning in the Age of Transhumanism* (pp. 224-236). Pennsylvania: IGI Global.
- Gondal, K. M. (2018). AI and educational leadership. *Annals of King Edward Medical University*, 24(4), 1-2. <https://doi.org/10.21649/akemu.v24i4.2591>
- Kelley, T., & Knowles, J. (2016). AI. In J. Britt Holbrook (Ed.), *encyclopedia of science, technology, and ethics* (2nd Edition, Vol. 1, pp. 180-182). Macmillan Reference USA.
- Khare, K., Stewart, B., & Khare, A. (2018). AI and the student experience: an institutional perspective. *IAFOR Journal of Education*, 6(3), 63-78. <http://dx.doi.org/10.22492/ije.6.3.04>
- Komalavalli, K., Hemalatha, R., & Dhanalakshmi, S. (2020). A survey of AI in smartphones and its applications among higher education students in and around chennai city. *Shanlax International Journal of Education*, 8(3), 89-95. <https://doi.org/10.34293/>
- Krippendorff, K. (2018). *Content Analysis: An Introduction to Its Methodology* (4th ed.). Sage Publications.
- Luckin, R. (2017). Towards AI-based assessment systems. *Nature Human Behaviour*, 1(3), 1-3. <https://doi.org/10.1038/s41562-016-0028>
- Merriam, S. B. (2013). *Qualitative Research: A guide for design and implementation* (Translation from 3rd Edition, Translation Editor: S. Turan). Ankara: Nobel Publishing.
- Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: an expanded sourcebook*. New York: Sage Publication.
- Nabiyev, V., & Erümit, A. K. (2020). Foundations of AI. In V. Nabiyev & A. K. Erümit (Eds.), *AI in Education from Theory to Practice* (pp. 2-37). Ankara: Pegem Akademi Publishing.
- Obschonka, M., & Audretsch, D. B. (2020). AI and big data in entrepreneurship: A new era has begun. *Small Business Economics*, 55(3), 529-539. <https://doi.org/10.1007/s11187-019-00202-4>
- Oliveira, M., Lopes, C., Soares, F., Pinheiro, G., & Guimaraes, P. (2020). What can we expect from the future? the impact of AI on society. *15th Iberian Conference on Information Systems and Technologies (CISTI)*, 1-6.
- Özgeldi, M. (2019). AI and Human Resources. In G. Telli (Ed.), *AI and the future* (pp. 198-222). Istanbul, Eastern Publishing House.
- Öztemel, E. (2020). AI and the future of humanity. *Information Technologies and Communication: The Future of Individuals and Society*, *Turkish Academy of Sciences*.
- Popenici, S. A., & Kerr, S. (2017). Exploring the impact of AI on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, 22(12), 1-13. <https://doi.org/10.1186/s41039-017-0062-8>
- Sariel, S. (2017). "AI today." In M. Karaca (Ed.), *Humanized Machines and AI* (pp. 21-25). Istanbul Technical University Foundation Journal.

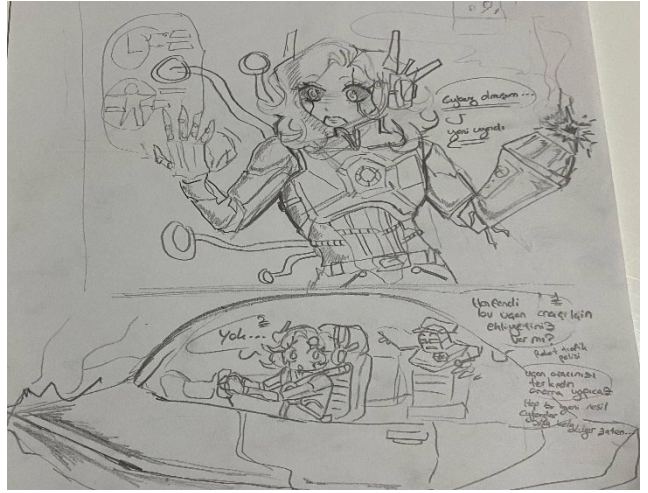
- Sheikh, S. (2020). *Understanding the role of AI and its future social impact*. Pensilvanya: IGI Global.
- Singh, G., Mishra, A., & Sagar, D. (2013). An overview of AI. *SBIT Journal of Sciences and Technology*, 2(1), 1-4. <http://dx.doi.org/10.13140/RG.2.2.20660.19840>
- Tamer, H. Y., & Övgün, B. (2020). Digital transformation office in the context of AI. *Ankara University Faculty of Political Sciences Journal*, 75(2), 775-803. <https://doi.org/10.33630/ausbf.691119>
- Taşkın, H., & Adalı, M. R. (2004). *Technological intelligence and competition strategies*. Sakarya: Degisim Publications.
- Taşçı, G., & Çelebi, M. (2020). A New Paradigm in education: AI in higher education. *OPUS-International Journal of Social Research*, 16(29), 2346-2370. <https://doi.org/10.26466/opus.747634>
- Tekgüç, U., & Adalier, A. (2019). Deep learning in education and applications. In A. Şişman, H. F. Odabaşı, & B. Akkoyunlu (Eds.), *Educational Technology Readings* (pp. 243-260). Ankara: Pegem Akademi Publishing.
- Teng, X. (2019, April). Discussion about artificial intelligence's advantages and disadvantages compete with natural intelligence. In *Journal of Physics: Conference Series* (Vol. 1187, No. 3, p. 032083). IOP Publishing.
- Uymaz, M. (2023). A Comparative analysis of gifted and typically developing secondary school students' perceptions of the future. *Sakarya University Journal of Education*, 13(3), 504-526. <https://doi.org/10.19126/suje.1380751>
- Xu, Z., & Yang, Q. (2012). Analyzing user retweet behavior on twitter. *IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining* (pp. 46-50).
- van Hooijdonk, R. (2017). *10 Technologies that could one day turn us all into real cyborgs*. Retrieved March 1, 2024, from <https://www.richardvanhooijdonk.com/blog/en/10>
- Yıldırım, A., & Şimşek, H. (2011). *Qualitative research methods in social sciences*. Ankara: Seçkin Publishing.
- Yılmaz, İ. (2012). *An AI application for staff planning in personnel planning (Thesis number: 387319)* [Master Thesis, Gazi University]. Turkish Council of Higher Education Thesis Center.
- Yin, R. K. (2009). *Case study methods: design and methods* (4th Edition). New York: Sage Publication.

Appendix-1

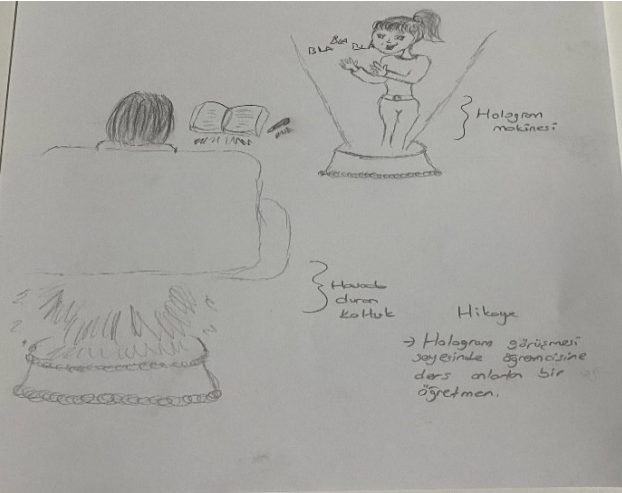
Pictures drawn by the participants



P-54



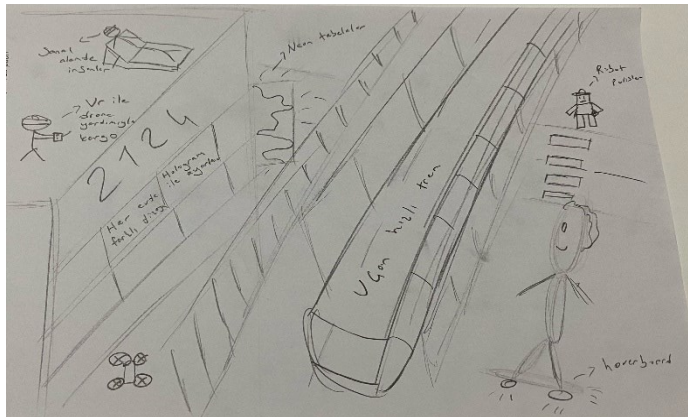
P-55



P-56



P-58



P-60

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Examination of Grade 7 Ratio Concept Tasks Designed by ChatGPT Based on Cognitive Demand Levels

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Abstract: The process that enables students to reach the gains in a mental and physical way while doing the mathematical tasks given under the supervision of the teacher is defined as an activity. The student's state of being active in the implementation process of the activities positively affects the permanence and efficiency of teaching. The process of creating tasks is a long and challenging journey as it involves a series of complex stages. Today, artificial intelligence technologies are utilized to facilitate this process. ChatGPT, one of the artificial intelligence tools, can support the teacher in preparing content, creating a lesson plan, evaluation process, etc., as well as supporting the teacher in creating activity design. It is important to understand how much the created tasks direct students to be cognitively active and to examine their cognitive demand levels in order to manage the teaching process efficiently and to improve the scope of the tasks. The aim of this study is to evaluate the tasks prepared for the 7th grade ratio concept through ChatGPT within the framework of cognitive demand levels. In the study, a case study design was utilized to examine the cognitive demand levels of the tasks created by ChatGPT 3.5 and ChatGPT 4, to determine the functionality of the activities, and to determine the deficiencies, if any, and how they can be eliminated. Content analysis was used to analyze the data obtained. It was concluded that the tasks created can be used by making necessary improvements, if any; thus, teachers can enrich their course content by saving time and energy. In this context, it is recommended to carry out tasks that will encourage the use of artificial intelligence tools by teachers in the world of education.

Keywords: Mathematical task, activity, cognitive demand level, ratio, chatgpt

1. Introduction

Numerous methods, techniques, and strategies are used to improve the quality of learning and teaching processes. Tasks, which are fundamental elements in achieving this goal, enable students to actively achieve the objectives both mentally and physically while performing mathematical tasks and additional activities either individually or in groups under teacher supervision (Nayir & Bulut, 2022). Tasks are designed, selected, or organized according to needs and aligned with learning objectives. The appropriate use of tasks in teaching processes holds significant importance. The tasks may aim to teach, reinforce, or evaluate a concept (Dede, Doğan, & Aslan-Tutak, 2021). Two perspectives on task use in mathematics education are notable. The concept of task involves problem-solving or activity processes related to a concept or subject that has been taught (Van de Walle et al., 2019), whereas the concept of activity focuses on making students active participants in learning a subject or concept (Dede, Doğan, & Tutak, 2020). From this perspective, tasks provide opportunities for students to develop skills such as reasoning and modeling in learning and teaching environments (Stein, Grover, & Henningsen, 1996).

Tasks inherently involve activity (Doyle, 1983); they not only enhance interaction, cooperation, and problem-solving skills (Atara et al., 2000) but also positively affect the retention and effectiveness of teaching (Lugosi & Urobi, 2022). Understanding the extent to which tasks engage students cognitively is crucial for managing teaching processes effectively and refining the scope of the tasks. Hence, determining the cognitive demand levels of the tasks is essential (Engin, 2015). The cognitive demand level was defined by Stein et al. (2000) as “the type and level of thinking required for students to successfully deal with and solve the task.” According to this framework, tasks are classified into four cognitive demand levels: “memorization tasks,” “procedures without connection tasks,” “procedures

with connection tasks,” and “doing mathematics tasks.” These levels are referred to as “cognitive demand levels.” Studies suggest that cognitive demand levels can decrease or increase during the preparation and implementation of tasks in the classroom (Engin, 2015; Henningsen & Stein, 1997; Sarpkaya, 2011; Stein et al. 1996). Appropriate cognitive demand levels need to be maintained during task preparation and implementation (Henningsen & Stein, 1997). Tasks should ideally involve higher-order cognitive thinking strategies to deepen students’ understanding of mathematical relationships and concepts (Stein et al., 2000). Therefore, tasks should be designed to maximize cognitive demands during preparation and implementation (Ecemiş, 2017; Ubuz et al., 2010).

Mathematical tasks typically serve three purposes: “teaching a concept,” “reinforcing a concept,” and “evaluating the learning of a concept” (Pekkan & Esmer, 2021). Designing mathematical tasks is pivotal in terms of process planning and operational paradigm. This involves analyzing and designing the objectives, determining the task design purposes, evaluating student knowledge, selecting relevant examples, drafting instructions, assessing tasks, and planning task implementation (Yeşildere, 2022).

Given the multifaceted nature of task preparation, leveraging tools that streamline this intricate and time-consuming process is essential.

Artificial intelligence technologies are instrumental in various demanding tasks such as coding, design of plans for content marketing, test creation, and data analysis. They are also employed in specialized domains such as disease diagnosis and case file preparation. They are being used in many fields from health to engineering, and from industry to marketing (Korucu & Biçer, 2020). These technologies are increasingly integrated into education, enhancing effectiveness and efficiency through capabilities such as generating exam questions, drafting education texts, providing detailed explanations, analyzing exam results, and employing diverse teaching techniques (Arslan, 2020). New concepts and professional groups have emerged with the development of artificial intelligence. Prompt engineering, a burgeoning discipline within artificial intelligence, focuses on optimizing instructions to ensure that artificial intelligence models provide appropriate responses (Breuss, 2023).

Artificial intelligence technologies, including chatbots such as ChatGPT, play a pivotal role in education by supporting student learning and alleviating teacher burdens in tasks such as question creation, content selection, and lesson planning (Pressey, 1950). The use of artificial intelligence technologies, such as personalized education, chatbots, intelligent agents, and artificial intelligence-supported assessment systems (Arslan, 2020), provides opportunities to improve the teaching processes such as personalized student learning and rapid response to diverse inquiries during lessons. Developed by OpenAI, ChatGPT is a dialogue-specialized artificial intelligence chatbot prototype (Kelly, 2022). The prompts presented as input to the system determine the scope of the output (Breuss, 2023). In other words, providing the input most appropriately for the desired output ensures that the resulting output is aligned with the intended goal.

Initially released as ChatGPT 3 in November 2022 (Edwards, 2023), ChatGPT 3.5 has since evolved with updated settings using supervised and reinforcement learning. The most recent OpenAI iteration is ChatGPT 4 (Terrasi, 2023). ChatGPT 3.5 is a freely available language model that uses deep learning to generate content similar to human-written text that can answer many questions (Scharth, 2022). It can also perform complex operations such as writing lyrics, writing poetry, and coding (Scharth, 2022). In comparison, ChatGPT 4 surpasses its predecessor, ChatGPT 3.5, by handling more complex inputs, including text, images, and videos, while delivering faster, more secure, and content-relevant responses (OpenAI 2023b). ChatGPT provides users with various responses aligned with their queries, enabling students to expand the scope of questions or explore different frameworks for answers. ChatGPT aids teachers in content creation, lesson planning, question formulation, evaluation processes, and task

design. Therefore, teachers can leverage artificial intelligence technologies to save time, enhance energy efficiency, and improve educational outcomes.

Creating tasks for classroom use is often challenging and time-intensive for teachers. To alleviate these challenges, the researchers prepared mathematical tasks using ChatGPT, one of the artificial intelligence tools, and examined their cognitive demand levels.

1.1 Aim of the Study

This study aimed to evaluate the tasks prepared by ChatGPT 3.5 and ChatGPT 4 for the Grade 7 ratio concept within the framework of cognitive demand levels. In line with this purpose, the study sought to answer the following questions:

1. How compatible are the tasks prepared by ChatGPT 3.5 and ChatGPT 4 with the given objective?
2. How suitable are these tasks for the given age group/grade level?
3. Do the tasks differ according to cognitive demand levels?

Additionally, the study aimed to identify the advantages and disadvantages of ChatGPT 3.5 and ChatGPT 4 versions in creating tasks.

2. Method

This was a qualitatively designed case study. A case study is a systematic design including steps such as collecting information, organizing the collected information, interpreting it, and reaching research findings. Its aim is to provide the best understanding of a situation rather than generalization (Denzin & Lincoln, 1994; Merriam, 1988). What distinguishes this method from many other research methods is its preference for understanding various topics in education, especially when questions of what, how, and why are asked (Çepni, 2012; Yin, 2003). This study used a case study design to examine the cognitive demand levels of the tasks created by ChatGPT 3.5 and ChatGPT 4, determine the functionality of the tasks, and identify the deficiencies and ways to address them.

2.1 Data collection

This study created tasks for the following objectives using two different versions of ChatGPT (3.5 and 4).

The relevant objectives from the Grade 7 curriculum related to the concept of ratio were as follows:

M.7.1.4.1 Determine the value the other will take if one of the multiplicities in the ratio is 1.

M.7.1.4.2 Find the other when one of the two multiplicities and the ratio between the multiplicities are provided.

Three different types of tasks were created: introduction, reinforcement, and evaluation. The prompts directed to ChatGPT during the task creation process were as follows:

1. What does the statement “Determine the value that one of the multiplicities in the ratio will take if one of them is 1” mean? Can you explain it with examples and an introduction and reminder task?
2. “Given one of two multiplicities in ratio to each other, find the other.” This objective belongs to the Grade 7 mathematics course. Can you think like a math teacher and prepare a deepening task related to this objective?
3. “Find the other when given one of two multiplicities their ratio to each other.” This objective belongs to the Grade 7 mathematics lesson. Now, can you think like a math teacher and prepare an assessment task related to this objective that we can use at the end of the lesson?

Each question was directed to both ChatGPT 3.5 and ChatGPT 4, resulting in six different tasks.

2.2 Data analysis

The content analysis method was used in this study. This involved bringing together similar data within the framework of certain concepts and themes and organizing and interpreting them in a way that is understandable to the reader (Creswell, 2012).

For the coding during the content analysis, the levels in the Task Analysis Guide (Stein et al., 2000) were used, as the Guide was deemed appropriate for the research purpose. The Guide was developed in line with a research project called QUASAR, conducted between 1990 and 1995. It was prepared to determine the cognitive demand level of hundreds of mathematical tasks found in the mathematics textbooks of the schools involved in the project and implemented in classrooms. The framework for coding the tasks according to cognitive demand levels, based on the Guide (Stein et al., 2000, p. 16, trans., Reçber, 2012), is presented in Table 1. The Guide contains a list of cognitive demand characteristics at each level and is used as a rating tool applicable to any mathematical task (Smith & Stein, 1998).

Table 1

Cognitive Demand Levels of Tasks Based on the Task Analysis Guide

LOW-LEVEL DEMANDS (LLD)	
Memorization Tasks (LLD-M)	The use of previously learned or given information, rules, or formulas involves remembering definitions. These tasks cannot be solved using a method because either no method exists to apply or the time interval is too short to apply a method. No ambiguity is involved. Such tasks are straightforward repetitions of previously learned material. The information to be repeated is clear and unambiguous. No association of the information, rules, formulas, or definitions with their underlying concepts and meanings is observed.
Procedures Without Connection (LLD-PC)	These tasks are algorithmic. The method to be used is explicitly requested or is evident from prior instruction or the context of the task. The cognitive demand for successful completion is limited. A little uncertainty exists regarding what to do and how to do it. No association with the underlying concept and meaning of the method used is observed. The focus is on producing correct answers rather than developing mathematical understanding. These tasks do not require an explanation or only require an explanation of the procedure.
HIGH-LEVEL DEMANDS (HLD)	
Procedures with Connection (HLD-PWC)	These tasks focus students' attention on the method to foster a deep understanding of mathematical concepts and ideas. They implicitly or explicitly suggest the application of general methods closely related to the underlying conceptual ideas. Often, these tasks present multiple representations, such as visual diagrams, dexterous situations, symbols, and problem situations. Making connections between multiple representations helps improve understanding. These tasks require a certain level of cognitive effort. Although general methods are followed, these tasks cannot be completed without a thinking process. Students need to engage with the conceptual ideas underlying the methods to be able to complete and understand the task.

Doing Mathematics Tasks
(HLD-DM)

These tasks require complex and non-algorithmic thinking, implying no clearly stated, repeated, predictable, or suggested approach in the task, its instructions, or examples. Students must explore and understand the nature of mathematical concepts, operations, and relationships. They need to observe and organize their own cognitive processes, access relevant knowledge and experiences, and use them appropriately in their work. Students must analyze the task, evaluate possible solution strategies, and consider the limitations of those solutions. Completing these tasks requires significant cognitive effort, and students may experience some anxiety due to the unpredictable nature of the solution process.

Source: Stein et al. (2000, p. 16).

Four levels of cognitive demands are defined in the Efficiency Analysis Guide, and their corresponding codes are presented in Table 2.

Table 2

Codes Used for Cognitive Demand Levels of Tasks

Level of cognitive demands	Abbreviation
LOW-LEVEL DEMANDS – Memorization Tasks	LLD-M
LOW-LEVEL DEMANDS – Procedures Without Connection	LLD-PC
LOW-LEVEL DEMANDS – Procedures with Connection	HLD-PWC
LOW-LEVEL DEMANDS – Doing Mathematics Tasks	HLD-DM

To enhance coding reliability, the first researcher coded the data initially, followed by an independent coding and comparison by the second researcher. Then, the coders discussed any discrepancies in the levels and reached a consensus on the common levels.

3. Findings

In this section, the findings from the analyzed data are examined within the framework of the questions posed to ChatGPT and then interpreted in relation to the research problems.

3.1 Question 1

QUESTION 1: *What does the statement “Determine the value that the other will take if one of the multiplicities in the ratio is 1” mean? Can you explain it with examples and an introductory and recall task?*

3.1.1 ChatGPT 3.5

The statement "Determine the value of one of the multiplicities in the ratio when one of them is 1" indicates that when one component of a ratio is set to 1, the corresponding value of the other component can be determined proportionally. This objective aims to gain a deeper understanding of the concept of ratio.

Introductory task: To introduce the lesson, the teacher can assign students a task where they calculate the ratios of different objects or scenarios. For example, students may be asked to determine the ratio of red balls to blue balls when 6 red and 12 blue balls are present in a box. This task helps students grasp how to determine the value of one component of a ratio when the other is set to 1.

Recall task: Following the lesson, the teacher should present students with various ratios and prompt them to explain which component's value is determined when one part is set to 1. Encouraging classroom discussion allows students to revisit the fundamental principles of proportion. Providing a

platform for students to exchange ideas helps them develop a deeper understanding of the concept of ratio.

3.1.2 ChatGPT 4

This objective involves understanding the characteristics of ratios and predicting the value of one part when the other is 1 in ratios.

3.1.2.1 Introductory Task: "Let's Make Pizza Together"

1. Before starting the lesson, students engage in a pizza-making task. Each student receives materials, such as cardboard pizza bases, glue, scissors, and colored paper.
2. Students are instructed to determine the amount of ingredients needed to make a pizza slice. For example, they can decide to use two sheets of green paper, one sheet of red paper, and one sheet of ...
- ... brown paper for each pizza slice. 3. Students calculate and record these ingredient proportions in a table.

3.1.2.2 Recall Task: "Pizza Slices on Sale!"

1. In the next class, students learn that each pizza slice sells for 2 dollars.
2. Students are asked to determine the cost of one slice of pizza based on the ratio and predict the cost if it were 1. They record their findings in a table.

Table 3

Cognitive Demand Levels of Introductory/Recall Tasks

Task Type	Introductory/Recall	
ChatGPT version	GPT 3.5	GPT 4
Cognitive demand level	LLD-M	HLD-PWC

When the introductory task prepared by ChatGPT 3.5 was analyzed within the framework of cognitive demand levels, it was determined to be at the level of LLD-M. This approach was chosen because, after presenting the initial situation for students to apply, a new but similar situation was given. Students were expected to apply the same approach again, essentially repeating the initial task. This repetition aligned with the characteristics of a memorization task.

The recall task from ChatGPT 3.5 was found to be at the level of HLD-PWC. This task required students to use their prior knowledge to explain and discuss the situation through examples, encouraging them to establish relationships between events and reason through different scenarios. This aligned with the level of connected methods.

Both tasks created by ChatGPT 3.5 for the first question were compatible with the content of the learning objective and appropriate for the age group/grade level. They effectively prepared content for student comparisons between units and included concrete elements.

For the tasks designed by Chat GPT 4, both the introductory and recall tasks were analyzed according to their cognitive demand levels and found to be at the level of HLD-PWC. In both tasks, students were expected to recognize the relationships between concepts using their basic knowledge. Creating a table with the new information required students to use multiple representations, demanding a certain level of cognitive effort.

The scope of both tasks created by ChatGPT 4 for Question 1 was also compatible with the content of the learning objective and the age group/grade level. These tasks provided students with the opportunity to analyze the relationships between the specified ratios and included examples from daily life, enhancing their understanding of the unit.

3.2 Question 2

QUESTION 2: “Find the other when given one of two multiplicities given their ratio to each other.” This objective belongs to the Grade 7 mathematics lesson. Now, can you think like a math teacher and prepare a deepening task related to this objective?

3.2.1 ChatGPT 3.5

Of course! Here is a math task that you can prepare to deepen the understanding of the statement “Given one of two multiplicities in proportion to each other, find the other.”

Task Name: Ratio-Based Puzzle

Target Objective: To develop the ability to determine one in proportion to another given their ratio.

Task Description:

1. Divide the class into four equal groups and provide each group with a piece of paper and a pencil.
2. Assign each group a question that involves determining one of two multiplicities based on a given ratio. For example: “There are 24 students in a class. Of these students, $\frac{3}{4}$ are girls. How many girls are there in the class?” In this question, $\frac{3}{4}$ represents the ratio of girls to total students. Students must calculate the number of girls based on this ratio. Note: You can also give different questions to other groups. In this way, each student will work on a different question, and at the end, they will share their answers.
3. Allow time for each group to solve their respective question using correct proportional reasoning on their paper.
4. Each group presents their solution to the class, explaining how they have arrived at their answer.
5. One student from each group will write their solution on the board or a large piece of paper and explain the process.
6. Students from other groups can ask questions and discuss their approaches to understanding the solution.
7. Review the correct answers together, addressing any misunderstandings or mistakes.
8. Conclude by offering additional examples or questions about ratios for further practice.

This task aims to enhance students’ critical thinking and problem-solving skills about ratios, while also fostering collaboration and discussion among peers.

3.2.2 ChatGPT 4

Of course! Here is a deepening task to help students master “Find one of the two multiplicities given their ratios to each other.”

Task Name: Ratio Puzzles

Objective: To enable students to understand the concept of ratios and develop their ability to find one of two multiplicities given their ratio to each other.

Materials:

- Paper and pencil

Event Duration: Approximately 15 min

Task Stages:**Step 1: Reminding the Concept of Proportion (5 min)**

In class, have a brief discussion with the students to review the concept of proportion. Review the definition of a ratio and demonstrate its use with examples. Ensure students understand the concept of ratios.

Step 2: Ratio Puzzles Questions (10 min) Ask students to take their paper and pencils and solve the ratio puzzles. They need to find the other multiple based on the given ratio in each question. You can adjust the difficulty level of the questions according to the students' needs. Here are some sample questions:

Question 1: In a restaurant, there are nine chairs at a table for six people. If another table has 12 seats, how many chairs should be at this table?

Question 2: Three tablespoons of coffee are used for one cup of coffee. How many cups of coffee can be made using nine tablespoons of coffee?

Table 4

Cognitive Demand Levels of Deepening Tasks

Task type	Deepening	
ChatGPT version	GPT 3.5	GPT 4
Cognitive demand level	LLD-M	LLD-PC

When the deepening task prepared by ChatGPT 3.5 was examined within the framework of the cognitive demand level, the task was found to be at the level of LLD-M. The main purpose of this task was to solve the question given in Step 2; in this step, students are expected to reach the answer using only basic knowledge rather than establishing a relationship between old knowledge and concepts. In the following steps of the task, students are suggested to discuss their answers. However, this discussion does not raise the level of the task, as it is more about checking the results rather than a new situation.

For Question 2, it was determined that the scope of the deepening task created with ChatGPT 3.5 was compatible with the content of the learning target and the age group/grade level. The content was designed to emphasize that a proportion occurred when two ratios were equal.

When this task prepared by ChatGPT 4 for the deepening task was analyzed according to the cognitive demand levels, it was evaluated as LLD-PC. The information requested by the question was present in prior knowledge and did not have any ambiguity. It focused on producing correct answers instead of developing a deeper mathematical understanding. However, the process design of the task was quite detailed, and it was thought to facilitate the teacher in shaping the lesson plan.

For Question 2, it was determined that the scope of the deepening task created with ChatGPT 4 was compatible with the content of the learning objectives and the age group/grade level, as it allowed the students to establish the relationship between two multiplicities and was supported by concrete examples.

3.3 Question 3

QUESTION 3: *“Find the other when given one of the two multiplicities and the ratio between them.” This objective belongs to the Grade 7 mathematics lesson. Now, can you think like a math teacher and prepare an evaluation task related to this objective for use at the end of the lesson?*

3.3.1 ChatGPT 3.5

Of course! Here is a math task that you can use to assess the understanding of “Given one of two multiplicities and the ratio of the two, find the other.”

Task Name: Ratio-Finding Questions

Objective: To evaluate the ability to find one of two multiplicities given the ratio of one to the other.

Task Description:

1. Arrange the class for individual work. Provide each student with a piece of paper and a pencil.

2. Hand out a test or worksheet with ratio-based questions. Sample questions include:

(a) A store has 120 apples and 80 oranges. What is the ratio of apples to oranges? (b) A basket contains 36 red, 48 green, and 72 blue balls. What is the ratio of red balls to green balls? (c) A music player contains 250 songs. If $\frac{3}{5}$ of these songs are rock songs, how many are pop songs? (d) A country has 500,000 men and 600,000 women. What is the ratio of men to women?

3. Encourage students to create their own real-life scenarios involving ratios and share these with the class. For example, they can discuss ratios related to product prices in a supermarket.

3.3.2 ChatGPT 4

Of course! Here is an assessment task for the skill of “Finding one of two multiplicities given their ratios.”

Task Name: Ratio Investigation

Objective: To evaluate students’ ability to use ratios to find one of the two multiplicities when the other is provided.

Materials:

-Paper and pencil

Event Duration: Approximately 15 min

Task Stages:

Step 1: Creating a Series of Questions (10 min)

Develop a set of questions that test students’ ability to find one of two multiplicities given its ratio to another. Sample questions:

Question 1: A team can clear an area of 9 m in 12 h. Given this ratio, how many meters can the same team clear in 15 h?

Question 2: There are 120 trees in a park. One-third of these trees are fruit trees. How many fruit trees are there?

Step 2: Solving the Questions (5 min)

Allow students time to solve the questions you have prepared. Ask them to find the unknown number using the given ratio. Have students write their solutions on their papers.

Table 5

Cognitive Demand Levels of Evaluation Tasks

Task Type	Evaluation	
ChatGPT version	GPT 3.5	GPT 4
Cognitive demand level	LLD-PC	LLD-PC

When the evaluation task created by ChatGPT 3.5 was analyzed according to the cognitive demand levels, it was found to be at the level of LLD-PC. The question content addressed the information available from prior learning, and the method to be applied was clear, causing the task level to remain at this level. In addition, the questions in the task were found to be answer-oriented rather than directing students toward higher-level thinking skills.

For Question 3, it was determined that the scope of the evaluation task created with ChatGPT 3.5 was compatible with the content of the learning target and the age group/grade level, as it established proportional relationships and included relevant instructions.

When the task prepared by ChatGPT 4 for the evaluation task was analyzed according to the cognitive demand levels, it was determined to be at the level of LLD-PC. The task focused on reaching the correct answer using basic knowledge rather than establishing relationships with different concepts. In addition, little uncertainty existed about what needed to be done in the task content.

For Question 2, it was determined that the scope of the evaluation task created with ChatGPT 4 was compatible with the content of the learning target and the age group/grade level. This task reinforced proportional thinking by having students first find the ratios by establishing a relationship between the given multiplicities and then equalizing them.

The cognitive demand levels of the tasks prepared by ChatGPT are summarized in Table 6.

Table 6

Cognitive Demand Levels of All Tasks

Task Type	Introductory/Recall		Deepen		Evaluation	
	GPT 3.5	GPT 4	GPT 3.5	GPT 4	GPT 3.5	GPT 4
Cognitive demand level	LLD-M	HLD-PWC	LLD-M	LLD-PC	LLD-PC	LLD-PC

As shown in Table 6, only one of the six tasks prepared by ChatGPT was at a high cognitive demand level. This meant that approximately 85% of the tasks remained at the LLD level. Two of the five tasks at the LLD level were at the memorization task level, and both tasks were created by ChatGPT 3.5.

When all the findings were evaluated, it was determined that ChatGPT could prepare mathematical tasks suitable for the targeted objective and grade level. However, the cognitive demand levels of the tasks it prepared remained at low levels.

3.4 Comparison of ChatGPT 3.5 and ChatGPT 4

When the task examples were analyzed, it was evident that the presentation style of the tasks differed according to the version. ChatGPT 4 offered a more systematic design, whereas the explanations made by ChatGPT 3.5 regarding the task level remained at a low level compared with ChatGPT 4. Conversely, the explanations provided by ChatGPT 3.5 were more comprehensive compared with that by ChatGPT 4. These differences between the explanations were seen when comparing the answers to the second question in both ChatGPT 3.5 and ChatGPT 4. This result aligned with the findings of Stojanov (2023). Although ChatGPT 4 explained the implementation process of the task briefly and clearly, ChatGPT 3.5 explained it more indirectly.

When the quality and content of the questions were evaluated, it was noticed that both versions failed to generate tasks related to high-level cognitive demand in mathematics. However, teachers were encouraged to facilitate classroom discussions based on student answers. In addition, both versions included explanations about the skills students would acquire after completing the tasks.

When evaluated within the framework of cognitive demand levels, the tasks prepared by ChatGPT 4 had higher cognitive demand levels. For example, in preparing an introductory task, the task designed by ChatGPT 3.5 was geared toward memorization (low demand levels), whereas the task prepared by ChatGPT 4 was designed for a connected method (high demand levels).

However, despite ChatGPT 4 being based on higher demand levels than ChatGPT 3.5, most of the tasks it prepared remained at low levels. For instance, when examining ChatGPT 4's deepening task design, it was found to be created according to the disconnected method tasks (low demand levels). Similarly, when analyzing the evaluation tasks, it is clear that both versions produced designs that included disconnected method tasks from low demand levels. Therefore, it was interpreted that ChatGPT 3.5 did not create a task design for high demand levels. However, ChatGPT 4 aimed for higher demand levels and did not fully achieve the task of doing mathematics.

In addition, both versions could not create task designs for high-level demand mathematics tasks, also known as doing mathematics tasks.

4. Conclusions and Discussion

In this study, ChatGPT, one of the artificial intelligence tools, was given the objectives that would constitute the course content, and instructions were given to prepare various types of tasks related to these objectives. The tasks created were then evaluated according to their cognitive demand levels. The analysis of the results showed that ChatGPT could design tasks appropriate to the age, grade, objective, and knowledge level of the students. Additionally, it provided various suggestions for the implementation of these tasks. In this context, it was determined that ChatGPT, as an artificial intelligence chatbot, could help teachers based on the content of the questions asked. Thus, while saving time and energy, teachers could enrich their course content. Artificial intelligence tools that can be considered teacher assistants (Brakina et al., 2021) can also be used for various functions, such as interactive games and creating custom questions, translating, and using them as language learning tools, which can actively engage students in the lesson. This situation brings advantages such as increased student motivation and a liberal approach to presenting their own ideas. Some studies reported similar results (Almelweth, 2022; Jones, 2021).

When the tasks prepared with ChatGPT 3.5 and ChatGPT 4 versions, which constituted the first research question, were examined, it was observed that the tasks were created in a way that would guide the teacher and allow for flexible modifications. In addition, it was possible to design the teaching process in different dimensions thanks to features such as changing the level of the tasks and adjusting them to be student-centered or teacher-centered. Thus, the task content could be developed according to the environment in which the task would be implemented; tasks that could adapt to the changes in the

teaching process could be implemented in the classroom. Considering the aforementioned situations, integrating artificial intelligence tools into lessons or using these tools to design course content can add different dimensions to the educational process (Arslan, 2020). Benefiting from artificial intelligence technologies also requires teachers to adapt to information technologies and encourage their students to learn in this direction (Yuan, 2022).

When evaluating the findings related to the second research question, which involved assessing the cognitive demand levels of the tasks prepared with both versions of ChatGPT, it was observed that the cognitive demands of the tasks remained at low levels. This situation suggested that teachers should expand the scope of the tasks or provide more comprehensive prompts to ChatGPT when preparing tasks. In addition, the fact that no tasks including the demand level of "Doing Mathematics Tasks" were created indicated that the chatbot had deficiencies in creating such tasks. In summary, ChatGPT 4 was found to generate tasks at higher demand levels compared with ChatGPT 3.5, but these tasks were not at sufficient cognitive demand levels.

As seen in the tasks created by ChatGPT, it was advantageous that the designed tasks could be directed, organized in a short time, flexibly adapted to the teaching strategy, and promote cooperation between students and teachers (Dwivedi & Joshi, 2021). The purpose of creating tasks was to provide conceptual understanding and foster a discussion process rather than merely assigning homework or solving questions (Özgen, 2017). Tasks that served a single purpose would lead to a uniform transfer of knowledge, causing students' interpretation and solution strategies to be similar and resulting in memorized knowledge (Özgen, 2017). Therefore, when designing tasks, it would be useful to include a guiding scheme for the type of tasks and their implementation in the process. Both ChatGPT versions could prepare content for the type of task asked. However, the tasks prepared by ChatGPT4 were found to be more systematic. The applicability of the prepared content can be considered as an indicator of its use as a helpful tool for teachers. In this way, teachers can save time and energy and enrich their course content. However, it is thought that it would be more beneficial for teachers to revise and use these tasks.

5. Recommendations

Today, it is clear that technology has ushered in a new era. The rapid advancement and the increasing number of artificial intelligence tools direct us to learn how to use these tools effectively. Therefore, it is suggested that efforts should be made to encourage teachers in the field of education to use artificial intelligence tools. These efforts can include in-service seminars or artificial intelligence courses. Moreover, introducing students to these tools and sparking their interest in coding may benefit their future technological developments. Researchers are recommended to conduct further studies on the role of artificial intelligence as a teacher assistant.

Although ChatGPT, which can be an assistant for the teacher, offers flexibility in the content it provides, some factors may be overlooked when applied in real-life situations. These factors include student psychology, classroom environment, and teacher psychology. As ChatGPT can design content independently of these factors, teachers need to consider that the designed content may include elements that do not directly address these factors. Therefore, teachers should revise and adapt the content as needed.

In addition, teachers and researchers who aim to maintain high cognitive demand levels in tasks are recommended to carefully consider those when creating prompts for ChatGPT. By doing so, they can ensure that the tasks generated align with their educational objectives and meet the desired cognitive demand levels.

References

- Almelweth, H. (2022). The effectiveness of a proposed strategy for teaching geography through artificial intelligence applications in developing secondary school students' higher-order thinking skills and achievement. *Pegem Journal of Education and Instruction*, 12(3), 169-176. <https://doi.org/10.47750/pegegog.12.03.18>
- Arslan, K. (2020). Artificial intelligence and applications in education. *The Western Anatolian Journal of Educational Sciences*, 11(1), 71-88. Retrieved from <https://dergipark.org.tr/en/pub/baebd/issue/55426/690058>
- Atara, S., Roberto, W. L., Woon, C., & Kamber, D. (2000). An implementation of active learning and its effect on the quality of student learning. *Innovations in Education and Training International*, 37(4), 381-389. <https://doi.org/10.1080/135580000750052991>
- Barakina, E. (2021). Digital technologies and artificial technologies in education. *European Journal of Contemporary Education*, 10(2), 285- 296. <https://doi.org/10.13187/ejced.2021.2.285>
- Breuss, M. (2023). *Prompt engineering: A practical example*. Retrieved from <https://realpython.com/practical-promptengineering/>
- Çepni, S. (2012). *Araştırma ve proje çalışmalarına giriş [Introduction to research and project work]*. Trabzon, Celepler Yayıncılık.
- Dede, Y., Doğan, M.F., & Aslan-Tutak, F. (Ed). (2020). *Matematik eğitiminde etkinlikler ve uygulamaları [Activities and applications in mathematics education]* (2nd Edition). Pegem Akademi, Ankara.
- Denzin, N. K., & Lincoln, Y. S. (Ed) (1994). *Handbook of Qualitative Research*. Thousand Oas, CA: Sage Publications.
- Doyle, W. (1983). Academic work. *Review Of Educational Research*, 53(2), 159-199. <https://doi.org/10.3102/00346543053002159>
- Dwivedi, V., & Joshi, Y. (2021). ICT perspectives of productive and sustainable development for 21st century higher education institutions. *International Journal of Education and Development using Information and Communication Technology*, 17(3), 81-96. Retrieved from <https://files.eric.ed.gov/fulltext/EJ1335689.pdf>
- Ecemiş, Ü. (2017). *An international comparison of the cognitive demand levels of tasks in Turkey's 5th grade mathematics books (Thesis Number: 481774)* [Master Thesis, Ankara University]. Turkish Council of Higher Education Thesis Center.
- Edwards, B. (2023). OpenAI's GPT-4 exhibits "human-level performance" on professional benchmarks. Retrieved from <https://arstechnica.com/information-technology/2023/03/openai-announces-gpt-4-its-next-generation-ai-language-model/>
- Engin, Ö. (2015). *A comparison of the cognitive demand levels of tasks in 7th grade mathematics textbook in Turkey with those in the national curriculum and the textbooks of other countries (Thesis Number: 396167)* [Master Thesis, Ankara University]. Turkish Council of Higher Education Thesis Center.
- Henningsen, M., & Stein, M. (1997). Mathematical tasks and student cognition: classroom-based factors that support and inhibit high-level mathematical thinking and reasoning. *Journal for Research in Mathematics Education*, 28(5), 542-549. <https://doi.org/10.5951/jresmetheduc.28.5.0524>

- Jones, J. (2021). Integrating machine learning in mathematics classroom. *Mathematics Teacher: Learning and Teaching PK-12*, 114(8), 624-628. <https://doi.org/10.5951/MTLT.2021.0001>
- Kelly, S. M. (2022, December 5). *This AI chatbot is dominating social media with its frighteningly good essays*. Retrieved from <https://web.archive.org/web/20221210112243/https://www.cnn.com/2022/12/05/tech/chatgpt-trnd/index.html>
- Korucu, A., & Biçer, H. (2022). *Eğitimde yapay zeka uygulamaları [Artificial intelligence applications in education]* (3rd ed.) Ankara: Pegem Publishing House.
- Lugosi, E., & Uribe, G. (2022). Active learning strategies with positive effects on students' achievements in undergraduate mathematics education. *International Journal of Mathematical Education in Science and Technology*, 53(2), 403-424. <https://doi.org/10.1080/0020739X.2020.1773555>
- Merriam, S. B. (1988). *Case study research in education: A qualitative approach*. San Francisco: Jossey-Bass.
- Nayir, Ö., & Bulut, S. (2022). Etkinlik kavramının matematik öğretimindeki tarihsel gelişimi [Historical development of the concept of activity in mathematics teaching]. *Eğitimde yapay zeka uygulamaları* (3rd ed.). Ankara: Pegem Yayınevi.
- OpenAI (2023b). *GPT 4 Technical Report*. Retrieved from <https://cdn.openai.com/papers/gpt-4.pdf>
- Özgen, K. (2017). Matematiksel öğrenme etkinliği türlerine yönelik kuramsal bir çalışma: Fonksiyon kavramı örnekleme [A theoretical study on types of mathematical learning activities: Function concept sampling]. *Abant İzzet Baysal Üniversitesi Eğitim Fakültesi Dergisi*, 17(3), 1437-1464. <https://doi.org/10.17240/aibuefd.2017.17.31178-338839>
- Pressey, S. L. (1950). Development and appraisal of devices providing immediate automatic scoring of objective tests and concomitant self-instruction. *The Journal of Psychology*, 29(2), 417-447. <https://doi.org/10.1080/00223980.1950.9916043>
- Reçber, H. (2012). *An international comparison of level of cognitive demands of the tasks in Turkey's 8th grade mathematics curriculum and textbook (Thesis Number: 342456)* [Master Thesis, Ankara University]. Turkish Council of Higher Education Thesis Center.
- Sarpkaya, G. (2011). *The investigation of mathematical tasks related to primary school secondary level algebra learning field in terms of cognitive demands: Mathematics course books and classroom implementations. (Thesis Number: 298508)* [Master Thesis, Gazi University]. Turkish Council of Higher Education Thesis Center.
- Scharth, M. (2022). *The ChatGPT chatbot is blowing people away with its writing skills*. The University of Sydney. Retrieved from <https://www.sydney.edu.au/news-opinion/news/2022/12/08/the-chatgpt-chatbot-is-blowing-people-away-with-its-writing-skill.html>
- Silver, E. A. ve Herbst, P. G. (2008). Theory in mathematics education scholarship. In F. K. Lester (Ed.), *Second handbook of research on mathematics teaching and learning* (pp. 39-68). Charlotte, NC: Information Age Publishing.
- Smith, M. S., & Stein, M. K. (1998). Reflections on practice: Selecting and creating mathematical tasks: From research to practice. *Mathematics teaching in the middle school*, 3(5), 344-350. <https://doi.org/10.5951/MTMS.3.5.0344>
- Stein, M. K., & Lane, S. (1996). Instructional tasks and the development of student capacity to think and reason: An analysis of the relationship between teaching and learning in a reform mathematics project. *Educational Research and Evaluation*, 2(1), 50-80. <https://doi.org/10.1080/1380361960020103>

- Stein, M. K., Smith, M. S., Henningsen, M., & Silver, E. A. (2000). *Implementing standards-based mathematics instruction: A casebook for professional development*. New York: Teacher College.
- Stojanov, A. (2023). Learning with ChatGPT 3.5 as a more knowledgeable other: An autoethnographic study. *International Journal of Educational Technology in Higher Education*, 20(35), 1-17. <https://doi.org/10.1186/s41239-023-00404-7>
- Terrasi, V. (2023). *GPT 4: How is it different from GPT 3.5?*. Search Engine Journal. Retrieved from <https://www.searchenginejournal.com/gpt-4-vs-gpt-3-5/482463/>
- Ubuz, B., Erbaş, A., Çetinkaya, B., & Özgeldi, M. (2010). Exploring the quality of the mathematical tasks in the new Turkish elementary school mathematics curriculum guidebook: the case of algebra. *ZDM Mathematics Education*, 5(42), 483-491. <https://doi.org/10.1007/s11858-010-0258-5>
- Wakhata, R., Mutarutinya, V., & Balimuttajjo, S. (2023). Exploring the impact of Stein et al.'s levels of cognitive demand in supporting students' mathematics heuristic problem-solving abilities. *Frontiers in Education*, 8, 1-13. <https://doi.org/10.3389/educ.2023.949988>
- Yeşildere, S. (2022). Matematiksel etkinliklerin tasarım ilkeleri. Eğitimde yapay zekâ uygulamaları [Design principles of mathematical activities. Artificial intelligence applications in education] (3rd ed) Ankara: Pegem Yayınevi.
- Yıldırım, A., & Şimşek, H. (2013). *Sosyal bilimlerde nitel araştırma yöntemleri [Qualitative research methods in the social sciences]* (9th ed.). Ankara: Seçkin Publishing House.
- Yin, R. K. (2003). *Case study research: Design and methods* (3rd ed.). Thousand Oaks, California: Sage.
- Yuan, Y. (2022). Quantitative analysis of Chinese classroom teaching activity under the background of artificial intelligence. *Education and Information Technologies*, 27(8), 11161-11177. <https://doi.org/10.1007/s10639-022-11080-x>

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Exploring The Role of Digital Literacy in University Students' Engagement with AI through the Technology Acceptance Model

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Abstract: Through the last decades, Artificial Intelligence (AI) has revolutionized the field of education and transformed traditional teaching approaches. This study aimed to examine how university students adopt AI tools in their learning processes and the role of digital literacy (DL) in this process through the lens of the Technology Acceptance Model (TAM). In this context, this study measured the impact of DL on university students' acceptance of AI technologies and their intention to use such technologies in the future. The data was collected from university students (N = 154) at a university in Western Türkiye during the fall semester of 2023. Data collection was conducted using two separate online forms; the first form included items adapted from the Digital Literacy Scale developed by Bayrakçı and Narmanlıoğlu (2021) to measure digital literacy levels, while the second form included items adapted from the UTAUT study by Venkatesh et al. (2003). The hypothesis testing results showed that students with higher levels of DL perceived the usefulness and ease of use of AI tools more positively, which positively affected their intention to adopt AI-based tools. The study also found that perceived usefulness and ease of use were important in shaping students' attitudes and behavioural intentions towards AI. When students perceive AI as a valuable tool for learning and find it easy to interact with, they are more willing to use it. This study suggests that DL plays a significant role in the acceptance of AI-based tools among university students, and accordingly, the TAM is a practical and accurate model to explore students' potential engagement with AI in the learning process.

Keywords: Digital Literacy, Artificial Intelligence, Technology Acceptance Model, University Students

1. Introduction

Artificial Intelligence (AI) has emerged as a groundbreaking technology in recent years, transforming traditional pedagogical approaches and learning environments. The integration of AI into education redefined and revolutionized the approaches adopted by educators in many forms, such as personalizing learning experiences, enhancing student engagement, and facilitating assessment and feedback mechanisms. This paradigm shift necessitates a digital literacy (DL) competency among university students since a certain level of DL competency is required to effectively integrate with AI technologies and maximize the use of these technologies. As Alakrash and Razak (2021) state, the recent increasing reliance on digital tools in education requires a profound understanding and acceptance of these tools among learners. Furthermore, DL competency offers proficiency in using technological tools and forms a ground to foster 21st-century skills such as flexibility, productivity, creativity, critical thinking, etc. In this context, The Technology Acceptance Model (TAM) offers a theoretical framework to examine this phenomenon, suggesting that the perceived ease of use (PEU) and perceived usefulness (PU) of technology can influence users' acceptance and engagement levels (Davis, 1989). Acceptance and effective use of AI-based tools can help students maximize learning outcomes, which makes TAM a relevant model in the AI-in-education context. Therefore, we argue that exploring DL's role in AI engagement through the lens of TAM can significantly contribute to how technology can be effectively adopted in educational settings.

Amidst this shifting educational paradigm, DL, which equips students with the necessary skills to navigate digital environments, has turned out to be a critical competence for university students. Furthermore, with the quick and intense integration of AI into education, the significance of DL has positioned from a mere familiarity to a deeper understanding and critical engagement with digital tools and environments. While the effective adoption and utilization of digital technologies are crucial in educational contexts (Aslan, 2021), it is evident that having a DL competency offers students a diverse set of skills, from critical thinking and problem-solving to communication and collaboration in digital environments (Bacalja et al., 2022; Bulganina et al., 2021). Recent developments in digital technologies show that DL is a supplementary skill that helps students step forward and is a foundational component in ever-evolving educational settings. Therefore, especially at the onset of the age of AI, it is essential to explore the intersection between DL and AI engagement to guide an informed decision-making process in any educational planning.

TAM has been used as a practical and seminal framework to understand how users accept and adopt technology. Introduced by Davis (1989), TAM posits that PU and PEU are significant determinants of individuals' intention to use a technology. This model has been used by researchers in educational contexts to reveal the nuances in student perceptions and behaviours in accepting new technologies (Jan & Contreras, 2011). It can be argued that TAM can be an instrumental tool in understanding the extent to which students interact or will possibly interact with the AI tools. It is also essential to explore this intersection with a particular focus on DL competence since it is a significant catalyst in the use of AI technologies (Wang et al., 2023). In this respect, TAM offers a powerful theoretical framework to fully understand the dynamics between DL competence and AI engagement of university students.

Although the use of AI technologies for educational purposes is becoming increasingly widespread, research on university students' acceptance and effective use of these technologies is limited. Especially within the framework of TAM, the acceptance of AI technologies and the role of DL in this process have not been adequately examined. In the current literature, there is a noticeable lack of an integrated model that considers these three important factors - TAM, AI interaction and DL. This gap is especially evident in the Turkish context. Considering all of the issues mentioned, it can be argued that studying the relationship between DL and AI engagement among university students can provide valuable insights for policymakers and practitioners. This is because the integration of AI into educational settings requires a fundamental level of DL. However, the degree to which DL influences the acceptance and use of AI among university students through the lens of TAM remains unexplored. Therefore, this study aims to address this gap in knowledge and provide valuable insights into the integration of AI into education, which is crucial for developing novel pedagogical approaches in higher education.

2. Related Literature

The integration of digital technologies into educational processes has led to a growing body of literature regarding the effectiveness of digital technologies in education, and TAM has been used as a convenient theoretical framework to explain this relationship. Therefore, literature can be categorized thematically under two themes as DL in education and TAM and user behavior.

DL in educational contexts has been a widely researched topic in literature. Researchers focused on exploring the role of DL from different perspectives, such as language teaching and learning (Aba Shaar et al., 2022; Alakrash & Razak, 2021; Liu, 2023), self-efficacy levels (Aslan, 2021; Gutierrez-Angel et al., 2022), challenges in implementing DL (Romero-Hall & Cherrez, 2023), factors that influence DL (Yoleri & Anadolu, 2022), student perceptions (Smith & Storrs, 2023), effects on global citizenship (Khlaisang & Yoshida, 2022) and active participation in society (Pegalajar Palomino & Rodriguez Torres, 2023), and higher order thinking capacities (Tian et al., 2023). The variety of topics studied indicates that DL has turned out to be one of the core concepts of education, influencing it from many different

perspectives. Most of these studies provide significant implications for the integration of DL into education and highlight the determining role of DL in increasing the quality of teaching and learning.

The implications of integrating DL into educational processes are multifaceted and transformative. The studies of Alakrash and Razak (2021) and Liu (2023) focus on the role of DL in language teaching and learning. Alakrash and Razak (2021) suggest the need for integrating digital technologies into the English language curriculum, emphasizing the shift towards technology-based teaching and learning paradigms, and they call for a transformation from traditional to digital modes of instruction to enhance language education's effectiveness and relevance in the digital age. Similarly, Liu's (2023) study underscores the importance of DL in language learning and emphasizes the role of DL in shaping the identities of language learners, which helps create inclusive learning environments. The studies of Aslan (2021) and Gutierrez-Angel et al. (2022) reveal the relationship between DL and self-efficacy of learners. They propose that higher education institutions should integrate comprehensive DL programs into their curricula to improve the self-efficacy of learners so that they can get ready for their future professional roles (Gutierrez-Angel et al., 2022) and targeted support and resources should be provided to students to enhance their DL self-efficacy (Aslan, 2021). The study of Tian et al. (2023) reveals the intersection between higher-order skills and DL, underscoring the role of educators in designing curricula that adapt teaching strategies based on students' digital experiences. The implementation of DL into education comes with several challenges. However, the study of Romero-Hall and Cherrez (2023) suggests that such challenges can be overcome with ongoing professional development and training and addressing DL challenges can enhance the effectiveness and resilience of faculty's digital pedagogy.

These studies emphasize the importance of integrating DL into education to foster a teaching and learning environment where digital tools are used as an aid. From facilitating the transition from traditional to digital instructional modes to fostering inclusivity and self-efficacy among learners, and finally, to empowering educators with strategies to overcome DL challenges, the evidence suggests a transformative potential of DL in education.

The Technology acceptance model has been used as a practical framework to explore users' level of interaction with emerging digital tools. Recently, TAM has been used in many studies to explore users engagement with AI in various fields such as agriculture (Mohr & Kuhl, 2021), construction (Na et al., 2023), commerce (Wang et al., 2023) and healthcare (Alhashmi et al., 2019). However, there have been very few attempts to explore the engagement level of learners with AI through the lens of TAM in educational settings. One of these studies conducted by Zou and Huang (2023) examined the acceptance of ChatGPT in second-language writing among graduate students using TAM and demonstrated that graduate students reported a high-level willingness to use ChatGPT in their writing process. Similarly, the study of Strzelecki (2023) also provides evidence for the acceptance of ChatGPT by university students. Another study by Li (2023) investigated the impact of AI-based systems on learning motivation through the lens of TAM and found that such systems positively influence student motivation, emphasizing the functionality of using TAM as a model to reveal student-AI engagement. The study of Zhang et al. (2023) utilizes TAM to discover pre-service teachers' engagement with AI with a special focus on determinant factors and gender-based differences. They suggest the encouragement of AI-powered in-service teacher education by addressing gender-specific aspects in AI acceptance. Lastly, Al Darayseh (2023) explored science teachers' perceptions to integrate AI applications into science education and highlighted that science teachers demonstrated a high-level of acceptance in the use of AI in their classrooms showing positive correlations with self-efficacy, attitudes, ease of use, intention to use and expected benefits. Although the studies conducted so far have been informative and insightful, there is still a need for more research to thoroughly investigate the level of engagement between students and AI across different educational environments.

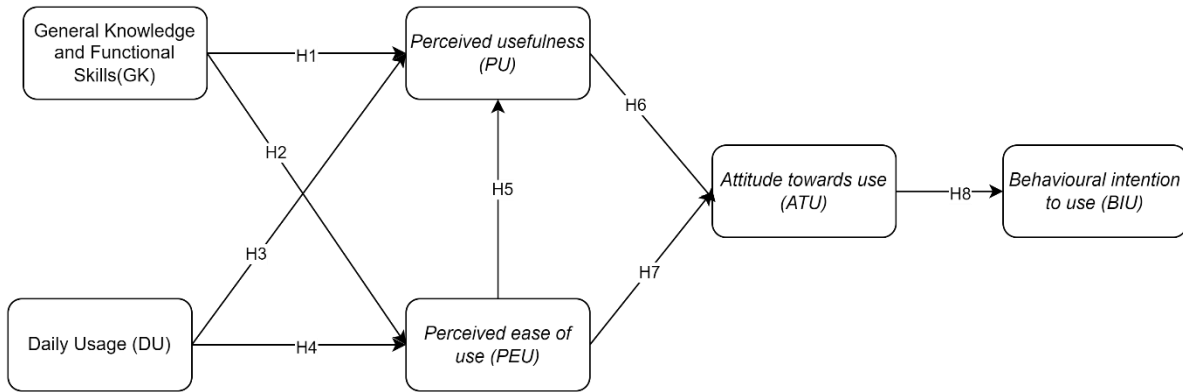
3. Methods

3.1. Proposed research model and hypotheses

In this study, we set out to investigate the impact of DL of university students (psychology and molecular biology and genetics students) on their acceptance of AI technologies and their intention to use these technologies by developing a model. Figure 1 shows the hypotheses of this study.

Figure 1

Research Model



3.2. Digital literacy (DL)

Koppel and Langer (2020) define DL as the essential technical skills needed for basic interactions with technology. DL encompasses a broad array of skills, such as media literacy, information literacy, and computer literacy. DL is based on the use of ICTs to search for, find, and utilize information (Mohammadyari & Singh, 2015). In this research, DL was modelled under two factors: (i) general knowledge and functional skills (GK) and (ii) daily usage (DU)

General knowledge and practical skills encompass a broad understanding of software, including information on software and hardware, digital technologies, licensed and pirated software, and malware. Additionally, technical proficiency is occasionally required for tasks such as formatting a computer, adjusting Proxy/DNS settings, and possessing both network and software expertise for more technical purposes. Today, the utilization of digital technologies is prevalent, involving aspects of e-citizenship, cloud technology, online streaming, reservations, online shopping, web browsing, and routine transactions. Below are the generated hypotheses indicating that higher DL level of students has a positive impact on the PU and PEU of AI technology:

- H1. GK positively affects PU.
- H2. GK positively affects PEU.
- H3. DU positively affects PU.
- H4. DU positively affects PEU.

3.3. Technology acceptance model (TAM)

TAM is a framework in the field of information systems that aims to explain how users adopt and utilize new technologies. Developed by Davis (1989), TAM posits that the success of a system depends on user acceptance, which is determined by three key factors: perceived usefulness (PU), perceived ease of use (PEU), and attitudes towards usage (ATU) of the system. The system is practically applied at the user level, where individuals interact with the technology. The decision to use technology is influenced by

behavioural intention (BIU), which is in turn, affected by attitude, representing the overall perception of the technology. The model suggests that if a system is not perceived as easy to use, it is unlikely to be considered useful. TAM elucidates that a user's perception of a system's usefulness and ease of use influences their intention to use or not use the system. Additionally, Davis (1989) emphasizes that practitioners use TAM to predict the acceptability of systems and diagnose the reasons for lack of acceptance, enabling them to take appropriate measures to enhance user acceptance.

The concept of PU pertains to an individual's belief in the extent to which the utilization of a specific technology will improve their performance or work results (Venkatesh & Bala, 2008). In essence, it revolves around the individual's assessment of whether employing the technology will enhance their proficiency in their tasks. The PEU pertains to an individual's perception of the extent to which utilizing a specific technology will require minimal effort, encompassing aspects of both learning and effectively using it (Venkatesh & Bala, 2008). PEU defines an individual's belief regarding the ease of comprehending and operating the technology. ATU pertains to an individual's comprehensive affective evaluation or sentiment regarding the utilization of a particular technology. This evaluation is influenced by their PEU and the PU of the technology (Davis, 1989). Behavioral intention to use (BIU) pertains to an individual's inclination to initiate and sustain the utilization of a particular technology (Davis, 1989). It can be understood as a forecast of their prospective actions derived from their present cognitive and affective states. Therefore, the following hypotheses will be tested with the data collected from the study group:

- H5: PEU positively affects PU.
- H6: PU positively affects ATU.
- H7: PEU positively affects ATU.
- H8: ATU positively affects BIU.

3.4. Instruction procedure

In this study, a vocational English course around the principles of task-based instruction (TBI) was designed to explore the engagement level of students with AI tools. TBI is a form of instruction where students are provided with real-world tasks and the assessment of task performance is made through task outcomes (Skehan, 1996). In this context, the tasks are designed to enable students to learn language structures through producing outputs using AI tools. In each task, a variety of AI tools were introduced to students to help them complete the tasks. At the beginning of the term, students were trained in the ethical and responsible use of AI tools in their tasks, and a guidelines document that frames how students can use AI tools in their work ethically was shared with the students (Appendix 1). The course content (Appendix 2) and a sample task description (Appendix 3) can be found in the appendices.

3.5. Data collection tools

We collected the data for this study using two distinct online forms. The first form includes demographic information about the students and items adapted from the Digital Literacy Scale (Bayrakci & Narmanlioğlu, 2021) to measure students' DL levels. The second form includes items adapted from the UTAUT study conducted by Venkatesh et al. (2003) (Appendix 4).

3.6. Data collection

The research target group is psychology ($n = 77$) and molecular biology and genetics ($n = 77$) students at a university in western Türkiye ($N = 154$). Data were collected in the fall semester of 2023 to identify participants' literacy levels, perceptions, and attitudes. The initial questionnaire gathered data on the

participants' demographic characteristics and DL levels. The subsequent questionnaire aimed to gauge the acceptance of technology for AI, utilizing a 5-point Likert-type scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). To assess reliability and comprehension, a small group of participants from a single institution underwent a pilot test. The first questionnaire was administered at the commencement of the fall semester, while the second was distributed at the end of the semester.

3.7. Data analysis

Questionnaires were distributed to over 250 students, yielding 214 responses. Following the exclusion of non-respondents and incomplete responses, data from 154 participants were deemed suitable for analysis. The proposed conceptual model underwent evaluation through structural equation modeling (SEM), with the analysis of the structural model conducted using Mplus (ver. 8.1) software. SEM is a robust statistical technique that is commonly used to study the relationship between observed and latent variables. Widely utilized across diverse scientific disciplines, SEM provides a comprehensive framework for testing and validating significant theories, particularly in assessing relationships between variables and constructing and evaluating structural models (Schumacker & Lomax, 1996).

3.8. Ethical principles

Ethics committee permission for this study was obtained from Balikesir University Social Sciences and Humanities Ethics Committee with the decision dated 23.01.2024 and numbered E.344791.

4. Findings

4.1. Measurement model results

This study evaluated the proposed conceptual model by calculating the properties of reliability and validity of the constructs. Item reliability and internal consistency for each construct were assessed using metrics such as Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE). Hair et al. (1995) recommended that values of Cronbach's alpha (α), CR, and AVE should be at least 0.7, 0.7, and 0.5, respectively. Based on the findings presented in Table 1, constructs demonstrated high reliability and internal consistency as Cronbach's α exceeded 0.7 (Taber, 2018). A CR value above 0.7 indicated satisfactory internal consistency and reliability across all constructs. Convergent validity was confirmed by examining the factor loading of each construct, with AVE values exceeding 0.5 for all constructs (Bagozzi & Phillips, 1982; Hair et al., 1995).

Table 1*Descriptive Statistics, Internal Consistency, Convergent Validity and Reliability of Items.*

Constructs	Item	Factor Loadings	Mean	Sd	Cronbach's α	CR	AVE
Daily Usage (DU)	DU1	.58	4.49	.78	.732	.72	.53
	DU2	.75	4.12	.89			
	DU3	.50	4.05	1.15			
	DU4	.51	3.40	1.37			
	DU5	.57	4.55	.65			
	DU6	.66	4.40	.90			
General knowledge and practical skills (GK)	GK1	.72	3.03	1.32	.889	.73	.61
	GK2	.72	3.09	1.15			
	GK3	.81	2.40	1.31			
	GK4	.75	2.91	1.39			
	GK5	.70	2.94	1.31			
	GK6	.68	2.32	1.42			
Perceived usefulness (PU)	PU1	.80	4.07	.88	.823	.69	.55
	PU2	.89	3.86	.89			
	PU3	.88	3.97	.88			
	PU4	.90	3.97	.93			
Perceived ease of use (PEU)	PEU1	.84	3.77	1.04	.958	.76	.87
	PEU2	.77	4.02	.93			
	PEU3	.74	3.74	1.03			
	PEU4	.83	3.57	1.02			
	PEU5	.90	3.71	1.04			
Attitudes towards usage (ATU)	ATU1	.91	2.86	1.23	.922	.74	.76
	ATU2	.96	3.35	1.19			
	ATU3	.94	3.77	1.04			
Behavioral intention to use (BIU)	BIU1	.61	4.00	1.01	.907	.72	.67
	BIU2	.76	4.06	1.01			
	BIU3	.95	4.11	.95			

In order to establish discriminant validity, it was observed that the square roots of the AVE values presented in Table 2 were greater than the correlations displayed below or to the left of them. This finding aligns with the criteria outlined by Hair et al. (1995) and confirms the discriminant validity of the measurement. The factors within the proposed model were identified to be correlated, as indicated in Table 2.

Table 2*Correlation Values for Each Factor*

	DU	GK	PU	PEU	ATU	BIU
Daily Usage (DU)	(.72)					
General knowledge and practical skills (GK)	.502*	(.78)				
Perceived usefulness (PU)	.220*	.454*	(.74)			
Perceived ease of use (PEU)	.443*	.425*	.541*	(.93)		
Attitudes towards usage (ATU)	.259*	.460*	.728*	.606*	(.87)	
Behavioral intention to use (BIU)	.170*	.284	.642*	.586*	.729*	(.82)

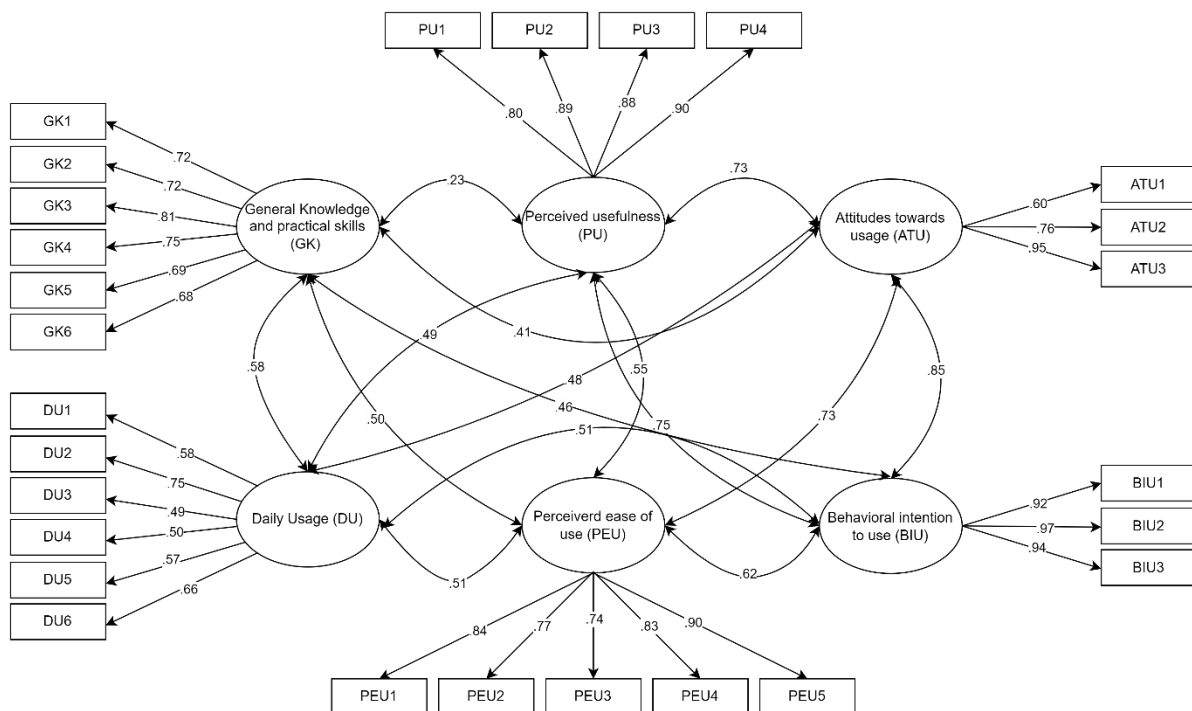
Note: * N= 154, p<.001

4.2. Validation of the measurement model

We employed confirmatory factor analysis (CFA) to evaluate the validity of the measurement by examining the extent to which a pre-established or constructed framework aligns with the gathered data. CFA, underpinned by theoretical foundations, is utilized to evaluate the consistency between the factors derived from multiple variables and the empirical data, as well as their alignment with the research sample. Consequently, CFA was applied to the measurement model depicted in Figure 2. The fit indices of the measurement are $\chi^2/df = 1.59$, $RMSEA = .067$ with 95% CI [.057 ~.077], $CFI = .925$, and $TLI = .915$, respectively. Regarding parameter values, the fit measures were within acceptable limits (Hu & Bentler, 1998; Schumacker & Lomax, 1996).

Figure 2

Confirmatory Factor Analysis

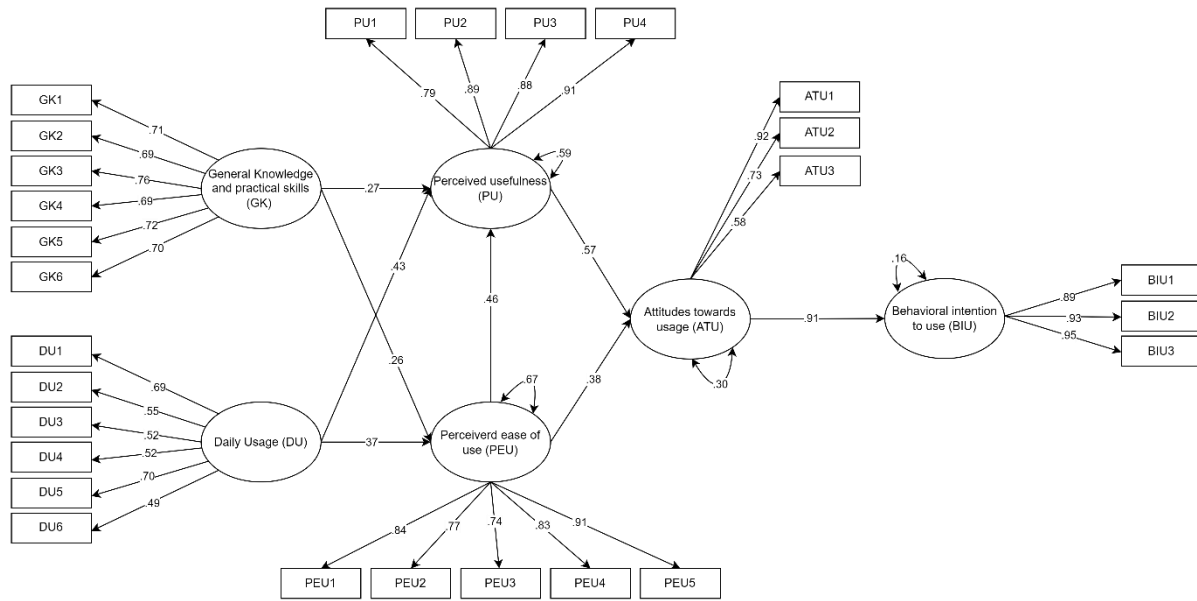


4.3. Structural model results

The research model's path coefficients were statistically analyzed and tested for significance using the SEM approach. The fit indices of the model $\chi^2/df = 1.52$, $RMSEA = .059$ with 95% CI [.048 ~.069], $CFI = .943$, and $TLI = .936$ respectively. Regarding parameter values, the fit measures were within acceptable limits (Hu & Bentler, 1998; Schumacker & Lomax, 1996). When Figure 3 is examined, a 16% variance explains the behavioural intention to use AI tools. In addition, the PU, PEU and, ATU structures of the model are explained with 59%, %67, and 30% variances, respectively.

Figure 3

Structural Equation Modelling of the Hypotheses



4.4. Hypothesis testing

The data presented in Table 3 indicates a notable positive correlation among these variables. All proposed hypotheses were validated within the model.

Table 3

Hypothesis Test Results

Structural relations of the proposed model	β	t	p-value	Decision
H1. GK → PU	.27	2.27	.024	Accepted
H2. GK → PEU	.26	2.22	.027	Accepted
H3. DU → PU	.43	2.93	.003	Accepted
H4. DU → PEU	.37	2.70	.007	Accepted
H5: PEU → PU	.46	4.53	< .001	Accepted
H6: PU → ATU	.57	5.71	< .001	Accepted
H7: PEU → ATU	.38	4.58	< .001	Accepted
H8: ATU → BIU	.91	7.90	< .001	Accepted

5. Discussion

The DL level of individuals is an essential determiner for their acceptance and utilization of technology in both personal and professional settings. It is well-established that individuals’ attitude towards technology is influenced by the extent to which they have DL skills (Mac Callum et al., 2014; Mailizar et al., 2022; Nikou & Aavakare, 2021). Accordingly, the acceptance of emerging technologies, such as AI-related tools, is directly related to individuals' DL levels. In this respect, this study hypothesized that DL levels of students, particularly General Knowledge and Practical Skills and Daily Usage domains, positively affect PU and PEU of AI tools in their learning process. The hypothesis testing results showed that General Knowledge and Practical Skills, and Daily Usage of digital tools significantly affect PU and PEU of AI tools. These results indicate that students who are more literate in digital technologies are likely to have a greater awareness of the capabilities of AI tools and, thus are more inclined to perceive AI as a useful tool for their learning process, which can lead to more favourable attitudes toward

adopting AI technologies because these students may be more aware of the specific benefits and applications of AI in their works (Li, 2023; Strzelecki, 2023; Zou & Huang, 2023). The positive relationships between GK/DU and both PU and PEU align with the foundational principles of the TAM because, according to TAM, both PU and PEU are primary predictors of the adoption of new technologies (Davis, 1989; Gie & Chung, 2019). In this respect, it can be suggested that improving DL can be a significant factor in encouraging university students to embrace the use of AI technologies in their learning process.

The hypothesis that the PU of AI positively influences ATU supports the idea that belief in the utility of a technology is a strong motivator for its acceptance (Davis, 1989; Kumar Kakar, 2017). The results of the analysis show positive path coefficients from PU to ATU. This result can be interpreted that when students recognize the practical benefits of AI in their learning process, they are likely to develop more positive attitudes towards its use (Ko & Leem, 2021). Similarly, the hypothesis about the relationship between PEU and attitudes toward use (ATU) suggests that the less effort required to use AI tools, the higher students' attitudes toward this technology may be. The results of the analysis show a positive relationship between PEU and ATU, which confirms this hypothesis. Ease of use can shape student attitudes by directly influencing the user's experience (Damerji & Salimi, 2021; Edmunds et al., 2012). If students find an AI tool intuitive, they are less likely to become frustrated or resist using it. As a result, they may evaluate AI technology more favourably and become more open to incorporating it into their learning process.

The last hypothesis tests that students' attitudes towards the use of AI tools (ATU) positively influence their behavioural intention to use AI (BIU) (Teo & Zhou, 2014). This hypothesis constitutes the most important link of the model because it explains the link between the affective components of technology acceptance and the behavioural components. The results of the analysis support this hypothesis with strong positive coefficients and show that students with positive attitudes towards AI are more likely to be willing to use it (Alzahrani, 2023; Gherheş & Obrad, 2018). Behavioural intention to use AI offers an important prediction of actual use. Positive attitudes can significantly support students' intentions to use AI tools, thus making ATU an important component of educational strategies aimed at promoting engagement with AI.

The results of the tested hypotheses confirmed the basic principles of the TAM and extended the coverage of these principles to the use of AI technology in education. The findings suggest that PU and ease of use directly influence students' attitudes towards AI and, consequently, significantly shape their intentions to use AI (Kashive et al., 2020; Ko & Leem, 2021). In light of these findings, the importance of a holistic approach to AI integration in education that addresses both cognitive and affective factors to encourage students' interactions with AI tools effectively comes to the fore. The findings of this study may help to draw important implications for the Turkish context. In Türkiye, the use of AI technologies in education is still in its early steps and the adaptation of university students to these technologies is a critical issue. This study found that Turkish university students' level of digital literacy significantly influences their tendency to accept and use AI technologies. This result provides evidence that higher education institutions in Turkey should develop policies in this direction.

In conclusion, the supported hypotheses revealed the importance of PU and ease of use in shaping students' attitudes towards AI tools. These attitudes are important in determining behavioural intentions towards AI. These implications can guide the development of educational policies that align with students' expectations, intentions, and uses of AI tools.

6. Conclusion

This study investigated the factors influencing university students' acceptance of AI tools in their learning process. The findings confirm the applicability of the TAM in the context of AI adoption for education. The study highlights the crucial role of DL, particularly general knowledge and daily usage, in fostering a positive perception of AI's usefulness and ease of use. Students with stronger DL are more likely to recognize the potential benefits of AI and find these tools user-friendly. This, in turn, leads to more favourable attitudes towards incorporating AI into their learning. Furthermore, the research emphasizes the importance of both PU and PEU in shaping students' behavioural intentions towards AI. When students perceive AI as a valuable tool for learning and find it easy to interact with, they are more likely to express a willingness to use it.

As the methodological implication of this study, it can be stated that The TAM provides a general framework for students' acceptance and adoption of new technologies. The model can also be used for testing various hypotheses. Although more studies are needed on the use of AI tools in educational settings, it is believed that positive outcomes can be achieved when students are guided on how to utilize these tools effectively. In particular, offering students a guide on AI ethics and how to utilize AI in the course content enhances the quality of student outcomes and their acceptance of this new technology.

References

- Aba Shaar, M. Y. M., Buddharat, C., & Singhasuwan, P. (2022). Enhancing students' English and digital literacies through online courses: Benefits and challenges. *Turkish Online Journal of Distance Education*, 23 (3), 154–178. <https://doi.org/10.17718/tojde.1137256>
- Al Darayseh, A. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: Artificial Intelligence*, 4, 100132. <https://doi.org/10.1016/j.caeai.2023.100132>
- Alakrash, H. M., & Razak, N. A. (2021). Technology-based language learning: investigation of digital technology and digital literacy. In *Sustainability*, 13(21),1-17. <https://doi.org/10.3390/su132112304>
- Alhashmi, S. F., Salloum, S. A., & Mhamdi, C. (2019). Implementing Artificial Intelligence in the United Arab Emirates Healthcare Sector: An Extended Technology Acceptance Model. *International Journal of Information Technology and Language Studies*, 3(3), 27-42. Retrieved from <https://journals.sfu.ca/ijitls/index.php/ijitls/article/view/107>
- Alzahrani, L. (2023). Analyzing students' attitudes and behavior toward artificial intelligence technologies in higher education. *International Journal of Recent Technology and Engineering (IJRTE)*, 11(6), 65–73. <https://doi.org/10.35940/ijrte.F7475.0311623>
- Aslan, S. (2021). Analysis of digital literacy self-efficacy levels of pre-service teachers. *International Journal of Technology in Education*, 4(1), 57–67. <https://doi.org/10.46328/ijte.47>
- Bacalja, A., Beavis, C., & O'Brien, A. (2022). Shifting landscapes of digital literacy. *Australian Journal of Language and Literacy*, 45(2), 253-263 <https://doi.org/10.1007/s44020-022-00019-x>
- Bagozzi, R. P., & Phillips, L. W. (1982). Representing and testing organizational theories: A holistic construal. *Administrative Science Quarterly*, 27(3), 459–489. <https://doi.org/10.2307/2392322>
- Bayrakci, S., & Narmanlioğlu, H. (2021). Digital literacy as whole of digital competences: scale development study. *Düşünce ve Toplum Sosyal Bilimler Dergisi*, 4, 1-30. Retrieved from <https://dergipark.org.tr/en/pub/dusuncevetoplum/issue/63163/945319>
- Bulgantina, S., V., Prokhorova, M. P., Lebedeva, T. E., Shkunova, A. A., & Mikhailov, M. S. (2021). Digital skills as a response to the challenges of the modern society. *Turismo-Estudios E Praticas*, 1, 1-7. Retrieved from <https://geplat.com/rtep/index.php/tourism/article/view/878>
- Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. *Accounting Education*, 30(2), 107–130. <https://doi.org/10.1080/09639284.2021.1872035>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Edmunds, R., Thorpe, M., & Conole, G. (2012). Student attitudes towards and use of ICT in course study, work and social activity: A technology acceptance model approach. *British Journal of Educational Technology*, 43(1), 71–84. <https://doi.org/10.1111/j.1467-8535.2010.01142.x>
- Gherheş, V., & Obrad, C. (2018). Technical and humanities students' perspectives on the development and sustainability of artificial intelligence (AI). *Sustainability*, 10(9), 3066. <https://doi.org/10.3390/su10093066>
- Gie, T., & Chung, J. F. (2019). Technology acceptance model and digital literacy of first-year students in a private institution of higher learning in Malaysia. *BERJAYA Journal of Services & Management*, 11, 103-116. <https://doi.org/10.5281/zenodo.2622329>
- Gutierrez-Angel, N., Sanchez-Garcia, J.-N., Mercader-Rubio, I., Garcia-Martin, J., & Brito-Costa, S. (2022). Digital literacy in the university setting: A literature review of empirical studies between 2010 and 2021. *Frontiers in Psychology*, 13, 1-35. <https://doi.org/10.3389/fpsyg.2022.896800>

- Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1995). *Multivariate data analysis (4th ed.): With readings*. Prentice-Hall, Inc.
- Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, 3(4), 424–453. <https://doi.org/10.1037/1082-989X.3.4.424>
- Jan, A. U., & Contreras, V. (2011). Technology acceptance model for the use of information technology in universities. *Computers in Human Behavior*, 27(2), 845–851. <https://doi.org/10.1016/j.chb.2010.11.009>
- Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology*, 38(1), 1–19. <https://doi.org/10.1108/IJILT-05-2020-0090>
- Khlaisang, J., & Yoshida, M. (2022). Empowering global citizens with digital literacy: modeling the factor structure. *International Journal of Instruction*, 15(4), 577–594. <https://doi.org/10.29333/iji.2022.15431a>
- Ko, Y.-H., & Leem, C.-S. (2021). The influence of ai technology acceptance and ethical awareness towards intention to use. *Journal of digital convergence*, 19(3), 217–225. <https://doi.org/10.14400/JDC.2021.19.3.217>
- Koppel, I., & Langer, S. (2020). Basic digital literacy – requirements and elements. *Práxis Educacional*, 16(42), 326–347. <https://doi.org/10.22481/praxisedu.v16i42.7354>
- Kumar Kakar, A. (2017). How do perceived enjoyment and perceived usefulness of a software product interact over time to impact technology acceptance? *Interacting with Computers*, 29(4), 467–480. <https://doi.org/10.1093/iwc/iwx006>
- Li, K. (2023). Determinants of college students' actual use of ai-based systems: An extension of the technology acceptance model. *Sustainability*, 15(6), 5221. <https://doi.org/10.3390/su15065221>
- Liu, G. (2023). To transform or not to transform? Understanding the digital literacies of rural lower-class efl learners. *Journal of Language Identity and Education*, 1–18. <https://doi.org/10.1080/15348458.2023.2236217>
- Mac Callum, K., Jeffrey, L., & Na, K. (2014). Factors impacting teachers' adoption of mobile learning. *Journal of Information Technology Education: Research*, 13, 141–162. <https://doi.org/10.28945/1970>
- Mailizar, M., Umam, K., & Elisa, E. (2022). The impact of digital literacy and social presence on teachers' acceptance of online professional development. *Contemporary Educational Technology*, 14(4), ep384. <https://doi.org/10.30935/cedtech/12329>
- Mohammadyari, S., & Singh, H. (2015). Understanding the effect of e-learning on individual performance: The role of digital literacy. *Computers & Education*, 82, 11–25. <https://doi.org/10.1016/j.compedu.2014.10.025>
- Mohr, S., & Kuhl, R. (2021). Acceptance of artificial intelligence in German agriculture: An application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture*, 22(6), 1816–1844. <https://doi.org/10.1007/s11119-021-09814-x>
- Na, S., Heo, S., Choi, W., Kim, C., & Whang, S. W. (2023). Artificial intelligence (AI)-based technology adoption in the construction industry: A cross national perspective using the technology acceptance model. *Buildings*, 13(10), 2518. <https://doi.org/10.3390/buildings13102518>
- Nikou, S., & Aavakare, M. (2021). An assessment of the interplay between literacy and digital Technology in Higher Education. *Education and Information Technologies*, 26(4), 3893–3915. <https://doi.org/10.1007/s10639-021-10451-0>
- Pegalajar Palomino, M. del C., & Rodriguez Torres, Angel F. (2023). Digital literacy in university students of education degrees in Ecuador. *Frontiers in Education*, 8, 1–8. <https://doi.org/10.3389/feduc.2023.1299059>

- Romero-Hall, E., & Cherrez, N. J. (2023). Teaching in times of disruption: Faculty digital literacy in higher education during the COVID-19 pandemic. *Innovations in Education and Teaching International*, 60(2), 152–162. <https://doi.org/10.1080/14703297.2022.2030782>
- Schumacker, R., & Lomax, R. (1996). *a beginner's guide to structural equation modeling* (2nd ed.). Psychology Press. <https://doi.org/10.4324/9781410610904>
- Skehan, P. (1996). A framework for the implementation of task-based instruction. *Applied Linguistics*, 17(1), 38–62. <https://doi.org/10.1093/applin/17.1.38>
- Smith, E. E., & Storrs, H. (2023). Digital literacies, social media, and undergraduate learning: What do students think they need to know? *International Journal of Educational Technology in Higher Education*, 20(1), 1–19. <https://doi.org/10.1186/s41239-023-00398-2>
- Strzelecki, A. (2023). Students' acceptance of chatgpt in higher education: an extended unified theory of acceptance and use of technology. *Innovative Higher Education*, 49, 223–245. <https://doi.org/10.1007/s10755-023-09686-1>
- Taber, K. S. (2018). The use of cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48(6), 1273–1296. <https://doi.org/10.1007/s11165-016-9602-2>
- Teo, T., & Zhou, M. (2014). Explaining the intention to use technology among university students: A structural equation modeling approach. *Journal of Computing in Higher Education*, 26(2), 124–142. <https://doi.org/10.1007/s12528-014-9080-3>
- Tian, X., Park, K. H., & Liu, Q. (2023). Deep learning influences on higher education students' digital literacy: The meditating role of higher-order thinking. *International Journal of Engineering Pedagogy*, 13(6), 33–49. <https://doi.org/10.3991/ijep.v13i6.38177>
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, 42(9), 1324–1337. <https://doi.org/10.1080/0144929X.2022.2072768>
- Yoleri, S., & Anadolu, Z. N. (2022). Examination of digital literacy skills of undergraduate students according to various variables. *Advanced Education*, 21, 121–134. <https://doi.org/10.20535/2410-8286.262190>
- Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education*, 20(1), 49. <https://doi.org/10.1186/s41239-023-00420-7>
- Zou, M., & Huang, L. (2023). To use or not to use? Understanding doctoral students' acceptance of ChatGPT in writing through technology acceptance model. *Frontiers in Psychology*, 14, 1259531. <https://doi.org/10.3389/fpsyg.2023.1259531>

APPENDIX

[Blinded] University
2023 – 2024 Academic Year (Fall)
Molecular Biology and Genetics Department
Vocational English IV (English)
Guidelines for Responsible Use of AI in Student Works

Guidelines for Using AI Tools in Student Tasks

Artificial Intelligence (AI) offers an array of solutions designed to mimic human intelligence with the intent to alter the educational landscape. The AI-powered chatbots (i.e., OpenAI's ChatGPT, Google's Bard or Microsoft's Bing) known as Large Language Models are tailored to simulate human conversation and offer tailored academic assistance. Acting as a peer, these LLM chatbots can swiftly answer queries, clarify doubts and provide guidance on any given subject, assisting in the learning process. LLM chatbots can act as a peer for educational purposes in several ways.

What CAN you do with AI Tools?

1. **Brainstorming Ideas:** You can use AI tools to brainstorm ideas by giving them a topic or keyword and asking them to generate ideas. For example, a student could ask an AI chatbot to generate ideas for a research paper or a creative writing assignment.
2. **Researching Topics:** You can use AI tools to research topics by giving them a topic and asking them to find relevant information. For example, you can ask an AI chatbot to find information about the life cycle of a butterfly.
3. **Understanding Concepts:** You can use AI tools to understand concepts by giving them a concept and asking them to explain it in a clear and concise way. For example, you can ask an AI chatbot to explain the concept of Cell Division or Freud's Iceberg Theory.
4. **Practicing Skills:** You can use AI tools to practice skills by giving them problems to solve and feedback on their work. For example, you can ask an AI chatbot to generate math problems for you to solve or multiple-choice grammar tests.
5. **Getting Feedback:** You can use AI tools to get feedback on your work by giving them your work and asking them for feedback. For example, you can ask an AI chatbot to give them feedback on your essay or presentation.

Ethical issues about the use of responsible AI:

One of the biggest ethical concerns surrounding the use of AI tools in homework is the risk of plagiarism. Plagiarism is the act of copying someone else's work without giving them credit. This includes copying text, ideas, or code from an AI tool without properly citing it.

You should use AI tools as a tool to help you learn, not as a way to cheat. It is important to remember that AI tools are trained on massive datasets of text and code, and they may sometimes generate text that is similar to existing work. This does not mean that the AI tool has plagiarized, but it does mean that you need to be careful and cite the sources properly. Therefore, while LLM chatbots and similar AI tools have enormous potential to assist learning, it's crucially important that these resources are not misused to bypass original thought and work.

The following are key points we need to focus on:

1. **Originality:** The use of AI should be an enhancement of your work - not a substitute for your original thoughts, ideas, and expressions. Therefore, you are encouraged to use the AI system to help develop ideas but must ensure that the final submission is your independent work.
2. **Responsibility:** While AI tools can provide information or draft responses, you must take responsibility for the learning outcomes. This involves critically examining, modifying, and incorporating AI-driven content into your own.
3. **Co-creation:** AI tools like LLM chatbots should be viewed as collaborators in the learning process, not as a contract cheating service.
4. **Citing AI Assistance:** Even as AI becomes more prevalent in education, it's important that you properly cite the assistance you receive from such tools. Failing to do so can lead to unintentional plagiarism.
5. **Authorship Accountability:** Even with AI assistance, you should retain accountability for their assignments' content, acknowledging that you understand and can discuss your submitted work.

I encourage you to use AI tools responsibly and ethically in your homework. Remember that AI tools are a tool to help you learn, not a way to cheat. When you use AI tools in your assignment, make sure to write in detail at the bottom of each assignment which AI tools you used and how you used them. This will help you to be transparent about your use of AI tools and avoid plagiarism. If you have received any help from any AI tool in your assignments, I expect you to write a description at the bottom of your assignments, as in the example below.

Template: *In this assignment, I used [name of AI tool] for [purpose] by issuing the following prompt ["the prompt"]. I collaborated with [name of AI tool] in the following way [collaboration detail]. I acknowledge that I have used AI as a collaborator in my assignment, that the assignment is my own, and that I take full responsibility for what I have written.*

Example: *In this assignment, I used the ChatGPT tool for brainstorming by giving the prompt "Create an outline to give me a presentation on cell division". I collaborated with ChatGPT in the following way: ChatGPT gave me an outline of the steps I could take to explain cell division. Using this outline, I determined the flow of the presentation. I acknowledge that I have used AI as a supporter in my assignment, that the assignment is my own, and that I take full responsibility for what I have written.*

[Blinded] University
2023 – 2024 Academic Year (Fall)
Molecular Biology and Genetics Department
Vocational English IV (English)
Course Content (Grade 3)

Course Name	Vocational English IV
Instructor	[Blinded]
Duration	14 Weeks (2 Hours)
Credit	2
Attendance	Compulsory (%70 attendance required)
Aim	The main objective of this course is to equip students with the necessary vocabulary related to their fields of study and enable them to develop a vocational literacy that aligns with the B1 and B2 levels outlined in the Common European Framework of Reference for Languages. Additionally, the course aims to keep students updated on contemporary developments in their respective fields.
Course Materials	Task-book provided by the course instructor
Instruction type	Task-based instruction
Assessment	Assessment of the course will be based on the mid-term and end-of-semester exams as well as assignments. Evaluation will be divided as follows: Mid-Term Evaluation: %40 (Exam 25 pts – Tasks 75 pts) End-of-Semester Evaluation: %60 (Exam 40 pts, Tasks 60pts)

Scope and Sequence

Week	Topic	Task	Language Focus	Grammar
Week 1	Negotiating course content.			
Week 2	Songs	Writing a song about genetics and recording using AI tools	Creating Imagery and Mood	Comparatives and Superlatives
Week 3				
Week 4	Fun Facts Quiz	Creating a multiple-choice fun facts quiz about genetics	Creating options and alternatives	Wh- Questions
Week 5				
Week 6	Crossword Puzzle	Creating a crossword puzzle on concepts related to genetics	Defining and describing	Relative Clauses
Week 7				
Week 8	Mid-Term Week			
Week 9	AI	Playing a “Guess What” game with ChatGPT	Asking questions to elicit information	Interrogative Sentences
Week 10				
Week 11	Astrology	Fortune-telling a friend’s future based on given data	Making predictions	Future Simple
Week 12				
Week 13	Fictional Character	Creating a fictional character based on pre-defined features	Describing	Adjectives and Adverbs
Week 14				

Week	Topic	Task	Language Function	Grammar
<i>Week 9</i>	AI	Playing a "Guess What" Game with ChatGPT	Asking questions to elicit information	Interrogative Sentences

Learning Objective

By the end of Week 9, students will be able to effectively use interrogative sentences to elicit information from ChatGPT about genetics-related topics. Students will practice formulating clear, concise, and relevant questions using ChatGPT voice chat.

Relevance and Context

This task leverages the interactive nature of ChatGPT to engage students in active learning. By crafting questions, students will not only explore using AI tools but also enhance their ability to communicate effectively and think critically about the responses they receive.

Instructions

Step 1: Prompt ChatGPT to play a GuessWhat game on genetics related topics. ChatGPT will think of a genetics-related thing and you will try to guess by asking questions.
Step 2: You need to play three games and ask different types of questions in each game, including Yes/No, Wh- and Tag questions.
Step 3: Using the voice chat of ChatGPT, play three games with ChatGPT.
Step 4: Submit the share link of the chat as your homework.

Deliverables

A log of your questions and ChatGPT's responses.

Performance Criteria

Success in this task will be assessed based on the accuracy and creativity of the crossword design, the clarity and grammatical correctness of the clues, and the strategic implementation of relative clauses in the clues.

Evaluation Rubric

Criteria	Excellent (25 points)	Good (15 points)	Needs Improvement
			(5 point)
Use of Different Types of Interrogatives	Skillfully uses a variety of interrogative forms including Yes/No, WH-questions, and Tag questions, demonstrating a nuanced understanding of how different questions elicit different types of information.	Utilizes some variety in interrogative forms but may rely more heavily on one type, showing a moderate understanding of eliciting information.	Primarily uses one type of interrogative form, indicating a basic or limited approach to eliciting information.
Correct Prompting	Questions are formulated correctly and clearly, prompting detailed and relevant responses from ChatGPT. Demonstrates an adept ability to guide the conversation through questions.	Questions are generally well-formed but may occasionally lack clarity or precision, leading to responses from ChatGPT that are less detailed or slightly off-topic.	Questions often lack clarity or grammatical correctness, resulting in vague or irrelevant responses from ChatGPT.
Quality of the Conversation	The conversation flows logically, with each question building on the last response to delve deeper into AI topics. Reflections and follow-ups are thoughtful, showing high engagement.	The conversation shows some logical progression, but there may be missed opportunities for deeper exploration or reflection on the responses.	The conversation lacks coherence, with little to no reflection on responses or follow-up questions, indicating a superficial engagement with the topic.

Appendix 4

Digital Literacy Survey Items (Turkish)

	Beni hiç yansıtmıyor	Beni çok az yansıtmıyor	Beni biraz yansıtmıyor	Beni çoğunlukla ansıtmıyor	Beni tamamen yansıtmıyor
Bölüm 1					
Günlük hayatta olduğu gibi dijital ortamlarda da kişisel veya yasal haklarımın (mahremiyet, telif, konuşma özgürlüğü vb.) devam ettiğinin farkındayım.					
Çevrim içi ortamlarda kendimin ve başkalarının kişisel verilerini (fotoğraf, adres, aile bilgileri vb.) korumak için nasıl davranmam gerektiğini bilirim.					
Çevrim içi ortamlarda eriştiğim bilgilerin doğru olup olmadığını farklı kaynaklardan sorgulayabilirim.					
Çevrim içi ortamlarda siber zorbalık (aşağılama, küfür, nefret söylemi vb.) ve istismar gibi davranışların etik ve yasal sorumluluklarının farkındayım.					
Bilişsel ve ahlakî gelişime uygun olan dijital oyunları ve içerikleri ayırt edebilirim.					
Çevrim içi ortamlarda yaptığım her şeyin kaydedildiğinin farkındayım.					
Dijital ortamlarda telif haklarının ihlalinden doğabilecek etik ve yasal sorumlulukların farkındayım.					
Bölüm 2					
Lisanslı yazılım, demo yazılım, korsan yazılım, kötü amaçlı yazılım ve crack kavramlarının ne olduğunu bilirim.					
Donanım ve yazılım teknolojilerinin ne olduğunu bilirim					
Bilgisayarına işletim sistemini kurabilirim/format atabilirim.					
Bilgisayarına ya da diğer elektronik cihazlarına yazılım veya program yükleyebilirim.					
Torent, İnternet, World Wide Web (WWW) ifadelerinin ne anlama geldiğini bilirim.					
Yasaklı İnternet sitelerine erişmek için cihazların proxy/dns ayarlarını değiştirebilirim.					
Bölüm 3					
e-Devlet uygulamalarını (MHRS, UYAP, vergi&ceza sorgulama vb.) etkin kullanabilirim.					
Bulut bilişim teknolojilerini (Google Drive, iCloud, Dropbox vb.) günlük hayatta etkin kullanabilirim.					
Mobil cihazlarda takvimi sadece tarihe bakmak için değil; aynı zamanda anımsatıcı, not alma, etkinlik oluşturma vb. işler için de kullanabilirim.					
Çevrim içi ortamlarda "video yüklemek/canlı yayın yapmak" gibi etkinliklerde bulunabilirim					
Rezervasyon, alışveriş, adres bulma vb. gündelik pratiklerde dijital teknolojileri etkin kullanabilirim.					
Kullandığım bir web sayfasını sık kullanılanlara veya yer imlerine ekleyebilirim.					
Bölüm 4					
Dijital teknolojilere dayalı yazılım/uygulama geliştirebilirim.					
Programlama dillerinden (Java, C, Visual Basic, PHP, vb.) en az birini kullanabilirim.					

Bölüm 5					
Uygulamaların kişisel bilgilerime (konum, rehber, kamera vb.) erişimini kısıtlamayı bilirim.					
İstenmeyen/spam epostaları ve ortalama mesajları tanıyıp engelleyebilirim.					
Sosyal ağlardaki paylaşımlarımda ve profilimdeki gizlilik/güvenlik ayarlarını değiştirebilirim.					
Nasıl güçlü bir şifre oluşturacağımın farkındayım.					
Bölüm 6					
Web tasarım sistemlerini (Weebly, Wordpress vb.) kullanarak İnternet sitesi tasarlayıp yayınlatabilirim.					
Kendi blog sayfamda veya farklı bloglarda yazı yazıp, paylaşabilirim.					
Dijital teknolojiler yardımıyla çeşitli imajları (fotoğraf, ses kaydı ve video vb.) değiştirip, yeni içerikler üretebilirim.					
Alanımla ilgili en az bir tane yazılımı (Photoshop, SPSS, Premiere, Office Word vb.) etkili bir şekilde kullanabilirim.					

Technology Acceptance Model Items (Turkish)

	Beni hiç yansıtıyor	Beni çok az yansıtıyor	Beni biraz yansıtıyor	Beni çoğunlukla ansıtıyor	Beni tamamen yansıtıyor
Yapay zekâ araçlarını kullanmak, öğrenme görevlerimi daha hızlı tamamlamayı sağlıyor.					
Yapay zekâ araçlarını kullanmak öğrenme performansımı artırıyor.					
Yapay zekâ araçlarını kullanmak öğrenme sürecimi daha verimli hale getiriyor.					
Yapay zekâ araçlarını kullanmak öğrenme sürecimi daha etkili hale getiriyor.					
Yapay zekâ araçlarını kullanmayı öğrenmek kolaydır.					
Yapay zekâ araçlarını kullanarak yapmak istediklerimi kolayca yapabiliyorum.					
Yapay zekâ araçlarını kullanırken çok fazla zorlanmıyorum.					
Yapay zekâ araçlarını kullanmada kolayca ustalaşabiliyorum.					
Yapay zekâ araçlarını kullanmayı kolay buluyorum.					
Yapay zekâ araçlarını kullanmaya başladığımda bırakamıyorum.					
Ödevlerimin yapay zekâ araçlarının kullanımını gerektiren yönleri olmasını sabırsızlıkla bekliyorum.					
Yapay zekâ araçları ile çalışmayı seviyorum.					
Bundan sonra, yapay zekâ araçlarını kullanmaya devam etmeyi planlıyorum.					
İleride, yapay zekâ araçlarını kullanmayı düşünüyorum.					
Gelecekte, yapay zekâ araçlarını kullanmayı planlıyorum.					

Article Information Form

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How Do Students Feel in Online Learning Platforms? How They Tell It: How Does Artificial Intelligence Make a Difference?

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Abstract: This study aims to investigate the effectiveness of an artificial intelligence (AI) model in determining students' emotional states during online courses and compares these AI-generated results with traditional self-report methods used in educational sciences. Conducted with 66 students from three different departments of a public university in Eastern Turkey during the 2021-2022 academic year, the study involved capturing facial images of students every 10 minutes during online lectures to analyze their emotional states using a deep learning-based CNN model. In addition, students provided their emotional states through a mood analysis form, which included personal information and subjective feelings such as happiness, sadness, anger, and surprise. The AI model achieved a high accuracy rate of 90.12% in classifying seven different emotional states, demonstrating its potential for real-time emotion recognition in educational settings. However, the study also found a 39% overlap between AI-determined emotional states and self-reported emotions. This finding emphasizes the need for a multifaceted approach to emotion measurement, integrating both advanced AI techniques and traditional self-report tools to more comprehensively understand students' emotional experiences. The results highlight the challenges and opportunities in combining technology with educational assessments and suggest directions for future research in improving emotion detection methodologies and their application in online learning environments.

Keywords: Emotions, Sentiment Analysis, Artificial Intelligence, Online Learning, Self-Report

1. Introduction

Distance learning has become significantly crucial on a global scale, particularly amidst the ongoing pandemic (Kim, 2020). The measures implemented during the crisis to sustain education using available resources are called emergency distance learning (Bozkurt, 2020). However, many teachers and students encountered distance learning for the first time. As a result of this experience process, the decrease in face-to-face interaction (Yolcu, 2020; Kumar et al., 2021; Sealy, 2021), the difficulty in keeping the motivation of the learners (Uçar, 2017; Gustiani, 2020), and the self-management and self-direction skills of the learners (Al-Taweel et al., 2020; Bozkurt, 2020) are listed as problems experienced in distance learning environments. Despite these limitations, developments in information and communication technologies offer important opportunities for formatting learning environments and increasing the motivation of learners (Pintrich, 2003; Bayrakçeken et al., 2021). In addition, these technologies are also used to determine the emotions of the students during e-learning. Research is being conducted on the effect of technology-enriched environments on student emotions (Imani & Montazer, 2019; Lacave et al., 2020). Additionally, certain features of these environments have specific effects on student emotions (Peng & Xu, 2020). There is also research on how emotions influence the use of self-regulation strategies (D'mello & Graesser, 2013; Taub et al., 2020). Finally, studies examine how students' emotions change during lessons (Sarrafzadeh et al., 2008; Bulut Ozek, 2018; Tonguç & Özkara, 2020; Hasnine et al., 2021).

When the literature is examined, several key areas of research can be identified. One area explores the effects of technology-enriched environments (Imani & Montazer, 2019; Lacave et al., 2020). Another focuses on how certain features of these environments impact students' emotions (Peng & Xu, 2020). Additionally, there are studies on the effect of emotions on the use of self-regulation strategies (D'mello & Graesser, 2013; Taub et al., 2020). Finally, research has been conducted on how students' emotions change during the lesson (Sarrafzadeh et al., 2008; Tonguç & Özkara, 2020; Hasnine et al., 2021). However, recent studies in education have emphasized the critical role of emotions in decision-making, timing, and managing learning activities (Zembylas, Theodorou, & Pavlakis, 2008; Yadegaridehkordi vd., 2019; Chevalère et al., 2023; Sydänmaanlakka et al., 2024; Yuan et al., 2024), and increasing the motivation of students in learning (Bouhlal, et al., 2020). It has been stated that cognition, motivation, and emotion, which have very interconnected structures in the learning process, are handled one by one in research, and especially emotion is the least studied component (Öztüre et al., 2021). However, research showed that there are connections between these groups such as success-emotions (Putwain, Becker, Symes, & Pekrun, 2018), emotions-learning strategies (Imani, & Montazer, 2019; Obergriesser & Stoeger, 2020), motivation-emotions (Martínez, et al., 2016), and emotions-commitment (Gömlüksiz & Kan, 2012). Aleven, McLaughlin, Glenn, and Koedinger (2016) argued that emotional attributes represent student characteristics that must be taken into account when designing adaptive online learning environments. Berikan (2020) stated that a lecture design that allows the use of emotions should be made to ensure social presence associated with teacher-learner interaction in online learning environments. Arzugül-Aksoy, Bingöl, and Bozkurt (2022) argue that emotions are one of the indicators of social existence that contribute to the formation of a meaningful learning experience.

As investigations into the impact of emotions within technology-enhanced learning environments on the learning process persist, it is argued that there is a need to understand how to design technologies to regulate emotions, especially in research during the pandemic (Graesser, 2020). In this context, the first requirement will be to determine the student's feelings. Scherer (2005) argues that when measuring emotions, one's self-report should be relied upon. However, Öztüre et al. (2021) stated that great advances have been made in neuroscience research on facial expression indicators, physiological indicators, and brain activity analysis, and these developments may contribute to studies on emotion. In addition, Eliot and Hirumi (2019) described the use of mostly self-report data collection tools as a limitation in determining emotions. The complexity of defining and measuring emotions in the educational context, given the intricate relationship between emotion and technology, has led to the use of various measurement approaches in research. Previous studies have utilized physiological measurements to assess emotions (Chandra & Calderon, 2005; Castro et al., 2009; Khezri et al., 2015; Mayer, 2020). Additionally, video and face analysis have been employed to determine emotions (Yoshitomi et al., 2000; Nicolaou et al., 2012; Taub et al., 2020; Wang et al., 2020; Schneider et al., 2022).

Artificial intelligence-based methods such as deep learning and machine learning have been used by various researchers for emotion identification from facial expressions. Artificial intelligence, which is called self-developing systems or machines that imitate human intelligence and can learn according to the information they collect, aims to create a more effective learning ecology in learning environments. Moreover, it facilitates the advancement of the learning process by enabling the collection, processing, reporting, and extraction of meaningful insights from big data within the digital environment. With the widespread utilization of artificial intelligence methods in education systems, it is easier to detect the motivating or distracting element based on physical or behavioral clues that motivate and distract students. Studies called sentiment analysis aim to determine the general emotions from facial expressions in Figure 1 using artificial intelligence techniques.

Figure 1*Examples of Seven Facial Expression Categories*

In recent literature, there has been a noticeable increase in studies conducted after 2019, with a preference for deep learning methods over machine learning. This preference stems from the ability of deep learning algorithms to learn and make accurate predictions through their data processing, facilitated by the artificial neural network structure, enabling automatic feature extraction (Maithri et al., 2022). For instance, Sakalle et al. (2021) and Savci and Das (2023) utilized the long short-term memory (LSTM) network to classify three basic emotions: positive, negative, and neutral. They compared the performance of various models including K-nearest neighbors (KNN), Multilayer Perceptron (MLP), LIB-Support Vector Machine (LIB-SVM), Support Vector Machine (SVM), and LSTM-based deep learning models for classification, achieving an impressive accuracy performance of 92.66% with 10-fold cross-validation.

Similarly, Chen et al. (2019) applied the Difference Convolution Neural Network (DCNN) approach on CK+ and BU-4DFE datasets to classify six basic facial expressions, demonstrating promising performance. Furthermore, Muhammad & Hossain (2021) proposed an emotion recognition system utilizing a convolutional neural network (CNN) model from facial expressions. Additionally, studies by Devi & Ch. (2021), Chowdary et al. (2021), Do et al. (2021), Li & Lima (2021), and Said & Barr (2021) employed deep learning approaches to accurately determine emotions from facial expressions, achieving accuracy rates exceeding 95%.

In the existing literature, there are limited studies analyzing facial expressions to evaluate the efficacy of online learning systems and students' level of engagement in learning environments. This gap highlights the need for further research in this area to better understand how students interact with and benefit from online learning platforms. By analyzing facial expressions, researchers can gain valuable insights into students' emotional states and engagement levels, which are crucial for improving the effectiveness of online education. Sethi and Jaiswal (2022) conducted a study where they classified students' facial images during lectures as "Understanding" or "Not Understanding" using a Convolutional Neural Network (CNN), Support Vector Machine, and Naive Bayes. Their findings suggest that deep learning methods like CNN may offer better performance in classifying facial images compared to other machine learning techniques such as SVM and Naive Bayes. Furthermore, Kaddoura and Gumaiei (2022) developed a deep learning model to predict student critical behavior continuously from facial expressions, aiming at real-time cheating detection during online exams. Maqableh et al. (2022) introduced a deep learning-based approach that utilizes facial expressions and heart rates to gauge students' engagement levels in learning environments. Lyu et al. (2022) proposed an automatic facial expression recognition method with transfer learning based on regional attention networks (RAN) to mitigate the impact of hand occlusion in students who inadvertently cover parts of their faces during online learning sessions. Their approach achieved an accuracy rate of 89% with the proposed architecture. Lastly, Bhardwaj et al. (2021) assessed student engagement in the online learning environment by analyzing facial expressions using CNN and calculating the average interaction score. Their study underscores the significance of emotion detection in determining student engagement during online learning sessions.

According to the findings derived from existing studies, it is evident that emotions play a crucial role in the learning process. This research endeavors to delve into the emotions experienced by students during lectures and, consequently, their engagement in online learning environments. Therefore, the main contributions of this paper include:

- To obtain quantitative data by designing an artificial intelligence model that can understand the emotions of students during the lesson
- Comparison of self-report methods commonly used in educational sciences and artificial intelligence methods such as deep learning to determine the emotional states of students' facial expressions. To our knowledge, this comparison represents the first attempt to determine emotional states in this manner.

In this research, the answers to the following questions will be answered based on the deep learning and face recognition measurement approach, which is one of the artificial intelligence approaches:

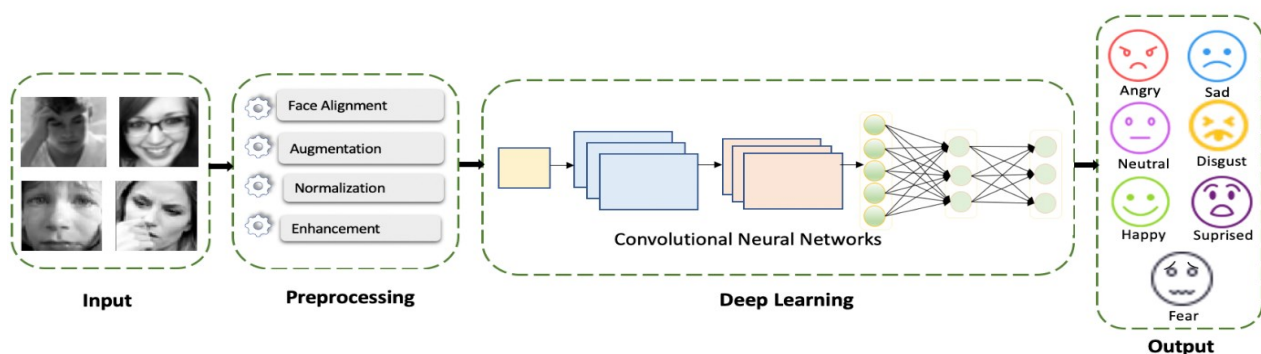
1. Which emotional states can be detected from the facial expressions of the students?
2. Do students' emotional states determined by face recognition match their self-reports?

2. Method

In this study, we investigated the emotional states of students to assess their engagement and motivation during an online lecture, where direct interaction between teachers and students is limited. To achieve this, we employed a two-pronged approach combining facial expression analysis with self-reported emotions. During the online lectures, students were encouraged to voluntarily turn on their cameras. Facial images were captured at 10-minute intervals to form a comprehensive dataset. This dataset included a range of facial expressions and hand movements, captured from various angles to enhance the robustness of our analysis. The facial images were then processed using a Convolutional Neural Network (CNN), a deep learning model known for its effectiveness in image classification tasks. Seven distinct emotional states—surprise, sadness, disgust, happiness, anger, fear, and neutral—were identified through the CNN model. To complement the facial expression analysis, students' emotional states were also evaluated using a self-report method. Students filled out a mood analysis form where they described their emotions during the lecture and provided reasons for their feelings. This self-report data provided an additional layer of insight into students' emotional experiences. The comparison of results from the CNN model and self-report forms allowed for a comprehensive analysis of students' emotional states. The CNN model's output was compared with the self-reported emotions to determine the level of agreement and discrepancies between the two methods. This approach highlights the potential of integrating advanced AI techniques with traditional self-report methods to gain a deeper understanding of emotional states in educational contexts. Figure 2 illustrates the block diagrams of the deep learning-based approach utilized in this study.

Figure 2

The Block Diagram of the Deep Learning-Based Model



2.1. Participants

The study involved 66 students (26 males and 39 females) from three distinct departments—Psychological Counseling and Guidance, Educational Technologies, and Science—at a state university in the eastern region of Turkey during the 2021-2022 academic year. This diverse participant pool was strategically chosen to enhance the study's generalizability and to provide a well-rounded perspective on student emotions and engagement in digital learning environments. Before the commencement of the study, participants were briefed on the research objectives and procedures, and all necessary ethical approvals were secured from the university's ethics committee. The participants were selected to represent a diverse cross-section of students to ensure a comprehensive understanding of emotional responses in online learning environments.

2.2. Data collection and analysis

Data collection and analysis were carried out using a two-pronged approach to comprehensively evaluate students' emotional states during online lectures. These are:

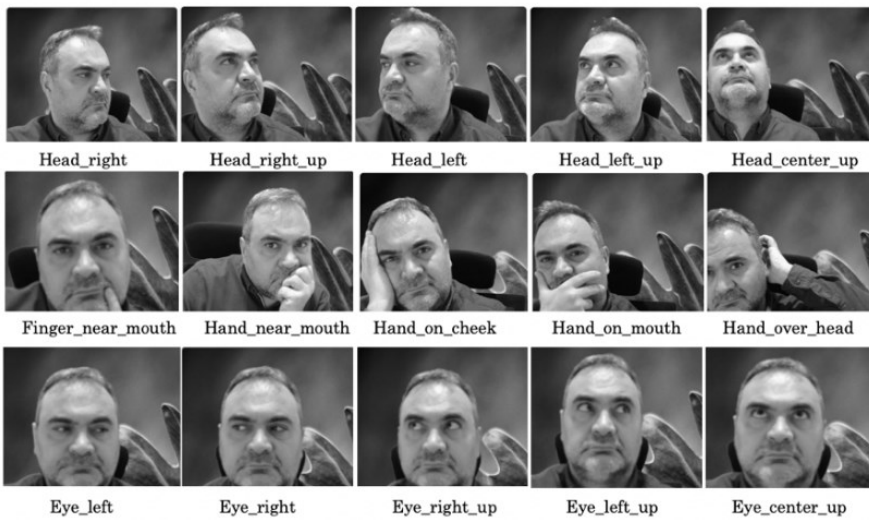
- *Facial Image Analysis:* The primary method involved the systematic collection of facial images from students during the online course. To capture a representative sample of students' emotional expressions, images were taken every 10 minutes throughout the lecture. This approach aimed to observe real-time changes in students' emotional states. Facial images were captured using screenshots from the online learning platform, with careful consideration given to various angles and positions to account for head movements and different viewing perspectives. The images were preprocessed to improve quality, including normalization and resizing to 48x48 pixels to reduce noise and distortion. The preprocessed images were then analyzed using a deep learning-based model, specifically a Convolutional Neural Network (CNN) with transfer learning. The CNN model, designed to detect seven distinct emotional states—surprise, sadness, disgust, happiness, anger, fear, and neutral—provided a quantitative assessment of students' emotions based on their facial expressions.
- *Self-Report Analysis:* Complementary to the facial image analysis, students were also asked to self-report their emotional states using a mood analysis form administered during the lecture. This form required students to indicate their current emotional state—such as happiness, sadness, anger, surprise, or any other relevant emotion—and provide a brief explanation for their feelings. This self-reporting method aimed to gather subjective data on students' emotions, allowing for a comparative analysis with the objective data obtained through facial expression analysis.

2.3. Deep learning-based model with transfer learning

Images of participants displaying various facial expressions were captured via screenshots. The objective was to analyze students' behavior and mood during e-learning sessions based on their facial expressions. The experiments lasted for a total duration of 75 minutes, with snapshots of the students taken every 10 minutes. As illustrated in Figure 3, students' heads are not consistently straight, and their eye movements vary.

Figure 3

Facial Expression with Hand Movements and Head Variations Captured Between 10 Minutes Intervals



It is observed that the students' heads move unevenly with their eyes, and sometimes they cover their mouths with their hands. These hand and eye movements may indicate that students are less interested in the lecture or are bored with e-learning. In order to provide more accurate training, these photos of students were also included in the training phase. It has also been preprocessed to improve the quality of the images and remove unwanted noise and distortion. In the preprocessing, the image was reduced to 48x48 size and normalized.

The Convolutional Neural Network (CNN), often regarded as the fundamental architecture of Deep Learning, comprises Convolution, Pooling, a Fully Connected layer, and a Classification layer. This model consists of multiple trainable components arranged sequentially and is followed by a training classifier. In the CNN architecture, the training process entails layer-by-layer operations after receiving input data. Subsequently, an output is generated and compared with the expected result. The disparity between the produced output value and the desired outcome yields the error, which is propagated to all weights through the backpropagation algorithm. To minimize this error, the weights are updated iteratively.

CNN has gained widespread adoption in computer vision applications in recent years. Transfer learning, a machine learning technique, involves reusing a model trained for one task in a related secondary task. With transfer learning, a base network trained on a large dataset is utilized, and in layers of this trained network are replicated as n layers of the target network. In pre-trained networks, the initial layer detects horizontal and vertical lines, while subsequent layers concentrate on features like edges and vertices. These networks specialize in specific image features in the final layers. Figure 4 illustrates the CNN architecture with transfer learning, while Table 1 provides a summary of the CNN model's layers and the parameters within these layers.

Figure 4

The Used CNN Architecture

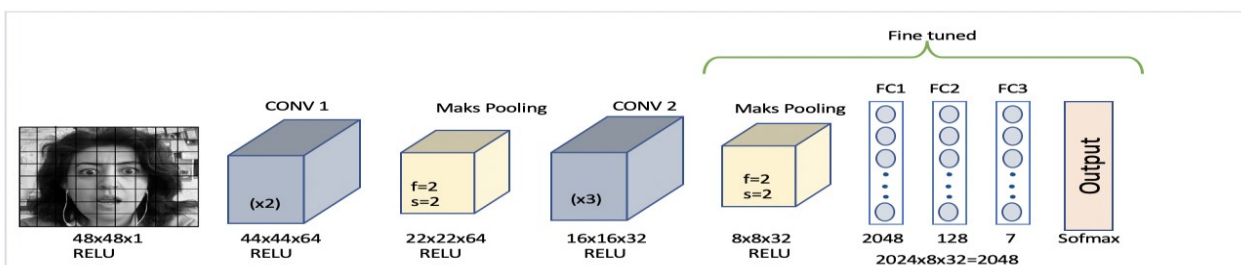


Table 1*The Parameters of the CNN Model*

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 46, 46, 64)	640
batch_normalization (BatchNo)	(None, 46, 46, 64)	256
activation (Activation)	(None, 46, 46, 64)	0
conv2d_1 (Conv2D)	(None, 44, 44, 64)	36928
batch_normalization_1	(Batch (None, 44, 44, 64)	256
activation_1 (Activation)	(None, 44, 44, 64)	0
max_pooling2d (MaxPooling2D)	(None, 22, 22, 64)	0
dropout (Dropout)	(None, 22, 22, 64)	0
conv2d_2 (Conv2D)	(None, 20, 20, 32)	18464
batch_normalization_2	(Batch (None, 20, 20, 32)	128
activation_2 (Activation)	(None, 20, 20, 32)	0
conv2d_3 (Conv2D)	(None, 18, 18, 32)	9248
batch_normalization_3	(Batch (None, 18, 18, 32)	128
activation_3 (Activation)	(None, 18, 18, 32)	0
conv2d_4 (Conv2D)	(None, 16, 16, 32)	9248
batch_normalization_4	(Batch (None, 16, 16, 32)	128
activation_4 (Activation)	(None, 16, 16, 32)	0
max_pooling2d_1 (MaxPooling2)	(None, 8, 8, 32)	0
dropout_1 (Dropout)	(None, 8, 8, 32)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 128)	262272
batch_normalization_5	(Batch (None, 128)	512
activation_5 (Activation)	(None, 128)	0
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 7)	903
activation_6 (Activation)	(None, 7)	0

2.4. Mood analysis form

The mood analysis form was designed to collect students' self-reported emotional states during the lecture. Students then reported their emotional state from a list of categories including happiness, sadness, anger, surprise, fear, disgust, and neutrality in addition to the personal information of the students. Additionally, they provided a brief explanation or justification for their chosen emotion, offering context or reasons behind their feelings. This form aimed to complement the facial expression data collected through the deep learning model, providing subjective insights that facilitated a comparative analysis with the objective data.

3. Findings

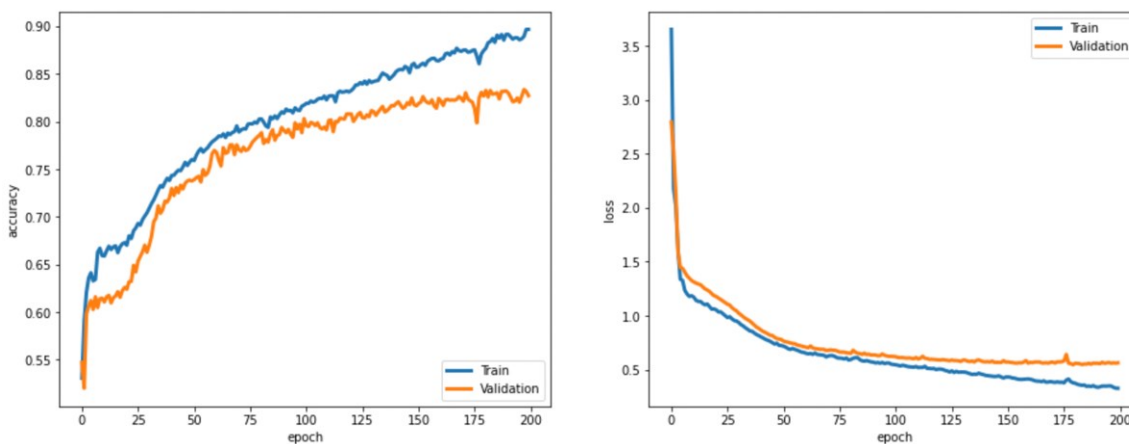
This section presents a comparative analysis of the study's findings, focusing on the effectiveness of various artificial intelligence techniques used for facial expression analysis and emotion recognition, as well as the accuracy of self-report emotion detection. The findings encompass the performance of the deep learning-based artificial intelligence model in detecting students' emotional states from facial expressions and compare these results with the students' self-reported emotions recorded through the mood analysis form. The analysis aims to highlight discrepancies and correlations between the AI-generated data and self-reports, offering insights into the strengths and limitations of each method in the context of online learning environments.

3.1. Detection of emotional states from facial expressions of students

In this study, students' emotional states were determined to determine their interest and motivation in online learning environments. The dataset is partitioned into 80% for training, 10% for validation, and 10% for testing purposes. Figure 5 depicts the loss and accuracy curves of the CNN model. In the study, seven different emotional states of the students were found with an accuracy value of 90.12%. There are many ways to measure the performance of the system in classification problems with deep learning. Accuracy and loss functions are among the most popular metrics. While accuracy quantifies the frequency of true predictions made by the classifier, the loss function assesses the error rate and performance of the model. This function computes the disparity between the model's prediction and the actual value, providing insight into the magnitude of deviation between them. Our study predicted seven different emotional states of the students with 90.12% accuracy.

Figure 5

The Loss and Accuracy Curves



During digital data collection, the fluctuation of students' emotions throughout the lecture was observed and recorded. Figure 6 shows the change in students' emotions during the 10-minute intervals of the lecture. Figure 7 shows the classification score of the emotional state for a sample student's facial expression.

Figure 6

The Change in Students' Emotions During the 10-Minute Intervals of the Lecture

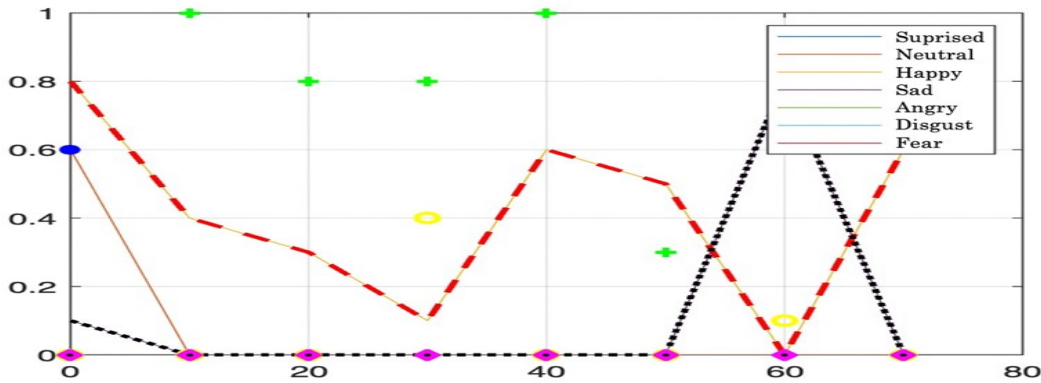
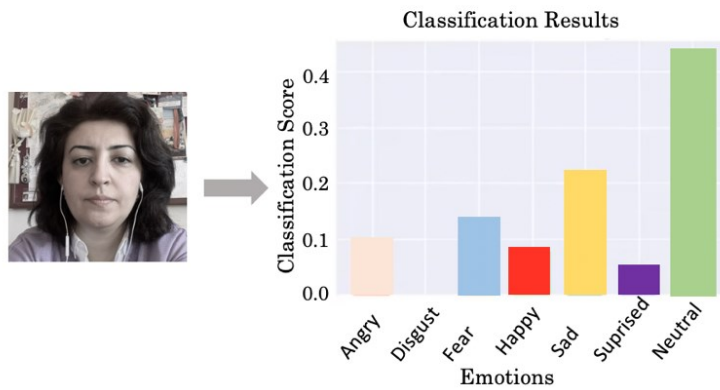


Figure 7

The Emotion Classification Score of a Sample Input



Classification result with the highest rate: Natural

3.2. Comparison of students' emotional states determined by face recognition and self-reports

In this step of the research, the quantitative data (emotional states) obtained with the deep learning-based artificial intelligence model were compared with the self-reports of the students as seen in Figure 8. For example, the student indicated with S1 stated in his/her self-report that he/she was generally sad in the course, surprised during the use of Web 2.0 tools, and did not feel afraid, angry, bored, or happy. It was determined that the self-report of this student and the data obtained with the artificial intelligence model did not match as seen in Table 2. As a result of the comparison, some of which are given in Table 2, it was determined that the self-reports of 26 students out of 66 students matched, but the quantitative data of the remaining 40 students did not match. This corresponds to approximately 39% of the students.

Figure 8

Example of a Student's Emotional State as Determined by Facial Recognition and Self-Reports



Table 2

Comparison of Artificial Intelligence Model and Self-Report Emotional State

Students	Emotion Detection with AI	Emotion Detection with Self-report	Match or not
S1	0.8 Happy, 0.2 Neutral	Sad	No
S2	0.9 Happy, 0.1 Neutral	Neutral	No
S3	0.7 Neutral, 0.2 Sad, 0.1 Fear	Neutral	Yes
S4	0.6 Sad, 0.4 Neutral	Happy	No
S5	0.8 Neutral 0.2 Happy	Neutral	Yes
S6	0.6 Neutral, 0.3 Surprised, 0.1 Fear	Neutral	Yes
S7	0.7 Sad, 0.1 Neutral, 0.2 Fear	Happy	No
S8	0.9 Happy, 0.1 Neutral	Fear	No
S9	0.4 Sad, 0.6 Neutral, 0.1 Fear	Neutral	Yes
S10	0.8 Neutral, 0.2 Fear	Neutral	Yes
S11
.....

4. Conclusion and Discussion

This research aims to determine the emotional states of students with the deep learning-based artificial intelligence model designed during an online course and to compare the obtained quantitative data with the self-report measurement method, which is frequently used in educational sciences. In the artificial

intelligence model developed to determine the emotions of the students during the course, a 7-class emotion detection experiment was carried out by using the Convolutional Neural Network, one of the deep learning models. When the studies in this field are examined, it is seen that data sets such as CK+, FER2013, and JAFFE are generally used in mood detection, and the performance of the system varies according to the dataset and deep learning models used. The reason for this is that the number of images in each emotion category varies between data sets. In addition, the performance of the system was affected by hyperparameters such as learning rate, hidden layers, iterations, and the selection of the activation function. Moreover, advancements in deep learning models and hyperparameter tuning play a crucial role in enhancing accuracy. In the Hua (2019) study, the emotion recognition study using the FER2013 dataset, 62.31% accuracy was achieved with the VGG19 model. Agrawal and Mittal (2020) achieved 65% accuracy using the CNN method on the same dataset. Liu et al. (2016) obtained 65.03% accuracy using the CNN-ensemble model.

In the CK+ dataset, Boughida et al. (2022) obtained an accuracy of 94.26% with the Gabor filter and Fallahzadeh et al. (2021) had 93.66% accuracy using AlexNet. Jaiswal and Nandi (2020) used the CNN method for the JAFFE dataset. They achieved a success performance of 64.32%. Hung et al. (2019) obtained an accuracy of 84.66% using VGG16 method. These variations underscore the importance of dataset selection and model customization in achieving high performance in emotion recognition tasks. In the study, instead of using ready-made data sets, a real data set was created by receiving facial images of the students at certain intervals of the course. This approach allowed for the collection of authentic and context-specific data, providing insights into real-world application challenges. With the CNN-based transfer learning model, the image classification performance was improved by using deep features, and a successful performance of 90.12% was achieved despite the small data set. The high accuracy demonstrates the potential of combining transfer learning with domain-specific data to enhance emotion recognition in educational settings.

The research findings revealed that there was a 39% overlap between the emotional states determined by artificial intelligence and those reported by the students themselves. This relatively low overlap suggests that while AI-based models can provide valuable insights, they may not fully capture the subjective nature of emotions as self-reports do. The determined rate is quite low. For this reason, although self-report measurement tools are accepted as reliable in the literature, it is thought that there is a need for diversity in data collection tools. However, upon reviewing the literature, it has been found that the majority of self-reported measurements in the field of education, particularly in the measurement of emotions, are conducted using instruments such as scales and questionnaires. Combining multiple data collection methods could offer a more comprehensive understanding of students' emotional states. Although Sherer (2005) emphasized the subjective aspect of emotion and stated that self-report should be trusted, he also stated that great progress has been made in neuroscience and artificial intelligence research and that these developments can contribute to studies on emotion. Öztüre, et al., (2021), argue that the relationships between emotion and technology in the educational context are multifaceted and this situation complicates the process of defining and measuring emotions.

This study contributes to the literature by integrating emotion and technology within the educational field, offering a new perspective on emotion recognition and its application in online learning environments. Mayer (2020) and Graesser (2020) specified that there is a need for research in the literature on how technologies should be designed to make sense of the cognitive and emotional processes during learning.

4.1. Limitations and future research

Recognizing emotions from facial expressions poses a significant challenge, as individuals may exhibit various emotions through the same facial expression. Open datasets available for emotion recognition are often insufficient and lack diversity. To improve the effectiveness of emotion recognition, a wider variety of data formats are required for training in deep learning models. Additionally, capturing facial expressions from multiple angles is essential for obtaining more accurate and reliable results. In the study, photographs of students at different moments and angles were taken during the course and their emotional states were determined from these photos. When the light conditions in the images change, the facial appearance can change, which greatly affects the results. In addition, occlusion, which is the situation where a certain part of the face is not visible or hidden, is one of the factors that cause the system to fail. It was observed that the students mostly covered their chin, mouth, or cheeks while listening to the course, which negatively affected the performance of the artificial intelligence trying to detect facial expressions. The limitations stemming from the quality of camera equipment and variations in the distance of students from the lens pose challenges in accurately capturing facial expressions in images. Additionally, the study's dataset is restricted to only 66 students, which limits the generalizability of the results. Future studies will aim to address this limitation by including larger and more diverse groups to enhance the robustness and generalizability of the findings. In addition, they could explore the integration of multimodal data, combining facial expressions with other indicators of emotional states, such as physiological measurements or behavioral data, to improve the accuracy and reliability of emotion detection in educational settings.

References

- Agrawal, A., & Mittal, N. (2020). Using CNN for facial expression recognition: a study of the effects of kernel size and number of filters on accuracy. *The Visual Computer*, 36(2), 405-412. <https://doi.org/10.1007/s00371-019-01630-9>
- Aleven, V., McLaughlin, E.A., Glenn, R.A., & Koedinger, K.R. (2017). Instruction based on adaptive learning technologies. In: *Handbook of Research on Learning and Instruction*, (2nd ed.). pp. 522–560. New York: Routledge.
- Al-Taweel, D., Al-Haqan, A., Bajis, D., Al-Bader, J., Al-Taweel, A. M., Al-Awadhi, A., & Al-Awadhi, F. (2020). Multidisciplinary academic perspectives during the COVID-19 pandemic. *The International Journal of Health Planning and Management*, 35(6), 1295-1301. <https://doi.org/10.1002/hpm.3032>
- Arzugül-Aksoy D., Bingöl, İ., & Bozkurt, A. (2022). Sorgulama Topluluğu Kuramı [Theory of Community of Inquiry]. *Açık ve Uzaktan Öğrenme Kuramları [Open and Distance Learning Theories]*, Ankara: Nobel Akademik Yayıncılık.
- Bayrakçeken, S., Oktay, Ö., Samancı, O., & Canpolat, N. (2021). Motivasyon Kuramları Çerçevesinde Öğrencilerin Öğrenme Motivasyonlarının Arttırılması: Bir Derleme Çalışması [Increasing Students' Learning Motivation within the Framework of Motivation Theories: A Compilation Study]. *Atatürk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 25(2), 677-698. Retrieved from <https://dergipark.org.tr/en/pub/ataunisobil/issue/62432/900664>
- Berikan, B. (2020). Çevrimiçi öğrenme ortamlarında öğrenen-öğretim elemanı etkileşimi [Learner-instructor interaction in online learning environments]. *Çevrimiçi Öğrenme Farklı Bakış Açıları*, Ankara: Pegem Akademi.
- Bhardwaj, P., Gupta, P. K., Panwar, H., Siddiqui, M. K., Morales-Menendez, R., & Bhaik, A. (2021). Application of deep learning on student engagement in e-learning environments. *Computers & Electrical Engineering*, 93, 107277. <https://doi.org/10.1016/j.compeleceng.2021.107277>
- Boughida, A., Kouahla, M. N., & Lafifi, Y. (2022). A novel approach for facial expression recognition based on Gabor filters and genetic algorithm. *Evolving Systems*, 13(2), 331-345. <https://doi.org/10.1007/s12530-021-09393-2>
- Bouhlal, M., Aarika, K., Abdelouahid, R. A., Elfilali, S., & Benlahmar, E. (2020). Emotions recognition as innovative tool for improving students' performance and learning approaches. *Procedia Computer Science*, 175, 597-602. <https://doi.org/10.1016/j.procs.2020.07.086>
- Bozkurt, A. (2020). Koronavirüs (Covid-19) pandemi süreci ve pandemi sonrası dünyada eğitime yönelik değerlendirmeler: Yeni normal ve yeni eğitim paradigması [Coronavirus (Covid-19) pandemic process and evaluations regarding education in the post-pandemic world: New normal and new education paradigm]. *Açıköğretim Uygulamaları ve Araştırmaları Dergisi*, 6(3), 112-142. Retrieved from <https://dergipark.org.tr/en/pub/auad/issue/56247/773769>
- Bulut Özek, M. (2018). The effects of merging student emotion recognition with learning management systems on learners' motivation and academic achievements. *Computer applications in engineering education*, 26(5), 1862-1872. <https://doi.org/10.1002/cae.22000>
- Castro, M.N., Vigob, D.E., Chu, E.M., Fahrner, R.D., Achaval, D., Costanzo, E.Y., Leiguarda, R.C., Nogueira, M., Cardinali, D.P., & Guinjoan, S. M. (2009). Heart rate variability response to mental arithmetic

- stress is abnormal in first-degree relatives of individuals with schizophrenia. *Schizophrenia Research*, 109, 134–140. <https://doi.org/10.1016/j.schres.2008.12.026>
- Chandra, A., & Calderon, T. (2005). Challenges and constraints to the diffusion of biometrics in information systems. *Communications of the ACM*, 48 (12), 101–106. <https://doi.org/10.1145/1101779.1101784>
- Chen, J., Lv, Y., Xu, R. & Xu, C. (2019). Automatic social signal analysis: Facial expression recognition using difference convolution neural network. *Journal of Parallel and Distributed Computing*, 131, 97–102. <https://doi.org/10.1016/j.jpdc.2019.04.017>
- Chevalère, J., Lazarides, R., Yun, H. S., Henke, A., Lazarides, C., Pinkwart, N., & Hafner, V. V. (2023). Do instructional strategies considering activity emotions reduce students' boredom in a computerized open-ended learning environment? *Computers & Education*, 196, 104741. <https://doi.org/10.1016/j.compedu.2023.104741>
- Chowdary, M. K., Nguyen, T. N., & Hemanth, D. J. (2021). Deep learning-based facial emotion recognition for human–computer interaction applications. *Neural Computing and Applications*, 35, 23311–23328. <https://doi.org/10.1007/s00521-021-06012-8>
- Devi, S. A., & Ch, S. (2021). An efficient facial emotion recognition system using novel deep learning neural network-regression activation classifier. *Multimedia Tools and Applications*, 80(12), 17543–17568. <https://doi.org/10.1007/s11042-021-10547-2>
- D'mello, S., & Graesser, A. (2013). AutoTutor and affective AutoTutor: Learning by talking with cognitively and emotionally intelligent computers that talk back. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 2(4), 1–39. <https://doi.org/10.1145/2395123.2395128>
- Do, L. N., Yang, H. J., Nguyen, H. D., Kim, S. H., Lee, G. S., & Na, I. S. (2021). Deep neural network-based fusion model for emotion recognition using visual data. *The Journal of Supercomputing*, 77, 10773–10790. <https://doi.org/10.1007/s11227-021-03690-y>
- Eliot, J. A., & Hirumi, A. (2019). Emotion theory in education research practice: An interdisciplinary critical literature review. *Educational technology research and development*, 67, 1065–1084. <https://doi.org/10.1007/s11423-018-09642-3>
- Fallahzadeh, M. R., Farokhi, F., Harimi, A., & Sabbaghi-Nadooshan, R. (2021). Facial Expression Recognition based on Image Gradient and Deep Convolutional Neural Network. *Journal of AI and Data Mining*, 9(2), 259–268. <https://doi.org/10.22044/jadm.2021.9898.2121>
- Gömleksiz, M. N., & Kan, A. Ü. (2012). Eğitimde duyuşsal boyut ve duyuşsal öğrenme [Affective dimension and affective learning in education]. *Electronic Turkish Studies*, 7(1), 1159–1177. Retrieved from <https://www.ajindex.com/dosyalar/makale/acarindex-1423933804.pdf>
- Graesser, A. C. (2020). Emotions are the experiential glue of learning environments in the 21st century. *Learning and Instruction*, 70, 101212. <https://doi.org/10.1016/j.learninstruc.2019.05.009>
- Gustiani, S. (2020). Students' motivation in online learning during covid-19 pandemic era: a case study. *Holistics*, 12(2), 23–40. Retrieved from <https://jurnal.polsri.ac.id/index.php/holistic/article/view/3029>
- Hasnine, M. N., Bui, H. T., Tran, T. T. T., Nguyen, H. T., Akçapınar, G., & Ueda, H. (2021). Students' emotion extraction and visualization for engagement detection in online learning. *Procedia Computer Science*, 192, 3423–3431. <https://doi.org/10.1016/j.procs.2021.09.115>

- Hung, J. C., Lin, K. C., & Lai, N. X. (2019). Recognizing learning emotion based on convolutional neural networks and transfer learning. *Applied Soft Computing*, 84, 105724. <https://doi.org/10.1016/j.asoc.2019.105724>
- Imani, M., & Montazer, G. A. (2019). A survey of emotion recognition methods with emphasis on E-Learning environments. *Journal of Network and Computer Applications*, 147, 102423. <https://doi.org/10.1016/j.jnca.2019.102423>
- Jaiswal, S., & Nandi, G. C. (2020). Robust real-time emotion detection system using CNN architecture. *Neural Computing and Applications*, 32(15), 11253-11262. <https://doi.org/10.1007/s00521-019-04564-4>
- Kaddoura, S., & Gumaei, A. (2022). Towards effective and efficient online exam systems using deep learning-based cheating detection approach. *Intelligent Systems with Applications*, 16, 200153. <https://doi.org/10.1016/j.iswa.2022.200153>
- Khezri, M., Firoozabadi, M., & Sharafat, A. R. (2015). Reliable emotion recognition system based on dynamic adaptive fusion of forehead biopotentials and physiological signals. *Computer methods and programs in biomedicine*, 122(2), 149-164. <https://doi.org/10.1016/j.cmpb.2015.07.006>
- Kim, J. (2020). Learning and teaching online during Covid-19: Experiences of student teachers in an early childhood education practicum. *International Journal of Early Childhood*, 52(2), 145-158. <https://doi.org/10.1007/s13158-020-00272-6>
- Kumar, N. N., Summerell, E., Spehar, B., & Cranney, J. (2021). Experiences of Honours Research Students and Supervisors During the COVID-19 Pandemic: A Pilot Study Framed by Self-Determination Theory. In *Frontiers in Education* (p. 389). Frontiers.
- Lacave, C., Velázquez-Iturbide, J. Á., Paredes-Velasco, M., & Molina, A. I. (2020). Analyzing the influence of a visualization system on students' emotions: An empirical case study. *Computers & Education*, 149, 103817. <https://doi.org/10.1016/j.compedu.2020.103817>
- Li, B., & Lima, D. (2021). Facial expression recognition via ResNet-50. *International Journal of Cognitive Computing in Engineering*, 2, 57-64. <https://doi.org/10.1016/j.ijcce.2021.02.002>
- Liu, K., Zhang, M., & Pan, Z. (2016, September). Facial expression recognition with CNN ensemble. In 2016 international conference on cyberworlds (CW) (pp. 163-166). IEEE.
- Lyu, L., Zhang, Y., Chi, M. Y., Yang, F., Zhang, S. G., Liu, P., & Lu, W. G. (2022). Spontaneous facial expression database of learners' academic emotions in online learning with hand occlusion. *Computers & Electrical Engineering*, 97, 107667. <https://doi.org/10.1016/j.compeleceng.2021.107667>
- Maqableh, W., Alzyoud, F. Y., & Zraqou, J. (2023). The use of facial expressions in measuring students' interaction with distance learning environments during the COVID-19 crisis. *Visual informatics*, 7(1), 1-17. <https://doi.org/10.1016/j.visinf.2022.10.001>
- Martínez, F., Barraza, C., Gonzalez, N., & González, J. (2016). KAPEAN: Understanding Affective States of Children with ADHD. *Educational Technology & Society*, 19(2), 18-28. Retrieved from <https://www.jstor.org/stable/pdf/jeductechsoci.19.2.18.pdf>
- Mayer, R. E. (2020). Searching for the role of emotions in e-learning. *Learning and Instruction*, 70, 101213. <https://doi.org/10.1016/j.learninstruc.2019.05.010>
- Muhammad, G., & Hossain, M. S. (2021). Emotion recognition for cognitive edge computing using deep learning. *IEEE Internet of Things Journal*, 8(23), 16894-16901.

- Nicolaou, M. A., Gunes, H., & Pantic, M. (2012). Output-associative RVM regression for dimensional and continuous emotion prediction. *Image and Vision Computing*, 30(3), 186-196. <https://doi.org/10.1016/j.imavis.2011.12.005>
- Obergriesser, S., & Stoeger, H. (2020). Students' emotions of enjoyment and boredom and their use of cognitive learning strategies-How do they affect one another?. *Learning and Instruction*, 66, 101285. <https://doi.org/10.1016/j.learninstruc.2019.101285>
- Öztüre, G., Fidan, A., Bakır, E., Uslu, N. A., & Usluel, Y. (2021). Eğitsel bağlamda teknoloji ve duygu çalışmaları üzerine bir sistematik haritalama çalışması: tanımlar, kuramlar ve gelecekteki yönelimler [A systematic mapping study on technology and emotion studies in educational contexts: definitions, theories and future directions.]. *Eğitim Teknolojisi Kuram ve Uygulama*, 11(1), 20-47. <https://doi.org/10.17943/etku.745236>
- Peng, X., & Xu, Q. (2020). Investigating learners' behaviors and discourse content in MOOC course reviews. *Computers & Education*, 143, 103673. <https://doi.org/10.1016/j.compedu.2019.103673>
- Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology*, 95(4), 667. <https://doi.org/10.1037/0022-0663.95.4.667>
- Putwain, D. W., Becker, S., Symes, W., & Pekrun, R. (2018). Reciprocal relations between students' academic enjoyment, boredom, and achievement over time. *Learning and Instruction*, 54, 73-81. <https://doi.org/10.1016/j.learninstruc.2017.08.004>
- Said, Y., & Barr, M. (2021). Human emotion recognition based on facial expressions via deep learning on high-resolution images. *Multimedia Tools and Applications*, 80(16), 25241-25253. <https://doi.org/10.1007/s11042-021-10918-9>
- Sakalle, A., Tomar, P., Bhardwaj, H., Acharya, D., & Bhardwaj, A. (2021). A LSTM based deep learning network for recognizing emotions using wireless brainwave driven system. *Expert Systems with Applications*, 173, 114516. <https://doi.org/10.1016/j.eswa.2020.114516>
- Sarrafzadeh, A., Alexander, S., Dadgostar, F., Fan, C., & Bigdeli, A. (2008). "How do you know that I don't understand?" A look at the future of intelligent tutoring systems. *Computers in Human Behavior*, 24(4), 1342-1363. <https://doi.org/10.1016/j.chb.2007.07.008>
- Savci, P., & Das, B. (2023). Prediction of the customers' interests using sentiment analysis in e-commerce data for comparison of Arabic, English, and Turkish languages. *Journal of King Saud University - Computer and Information Sciences*, 35(3), 227-237. <https://doi.org/10.1016/j.jksuci.2023.02.017>
- Scherer, K. R. (2005). What are emotions? And how can they be measured?. *Social science information*, 44(4), 695-729. <https://doi.org/10.1177/0539018405058216>
- Schneider, S., Krieglstein, F., Beege, M., & Rey, G. D. (2022). The impact of video lecturers' nonverbal communication on learning-An experiment on gestures and facial expressions of pedagogical agents. *Computers & Education*, 176, 104350. <https://doi.org/10.1016/j.compedu.2021.104350>
- Sealy, M. K. (2021). Communication in the Time of COVID-19: An examination of imagined interactions and communication apprehension during the COVID-19 Pandemic. *Imagination, Cognition and Personality*, 41(2), 158-186. <https://doi.org/10.1177/02762366211021076>

- Sethi, K., & Jaiswal, V. (2022). PSU-CNN: prediction of student understanding in the classroom through student facial images using convolutional neural network. *Materials Today: Proceedings*, 62, 4957-4964. <https://doi.org/10.1016/j.matpr.2022.03.691>
- Sydänmaanlakka, A., Häsä, J., Holm, M. E., & Hannula, M. S. (2024). Mathematics-related achievement emotions – Interaction between learning environment and students' mathematics performance. *Learning and Individual Differences*, 113, 102486. <https://doi.org/10.1016/j.lindif.2024.102486>
- Taub, M., Sawyer, R., Smith, A., Rowe, J., Azevedo, R., & Lester, J. (2020). The agency effect: The impact of student agency on learning, emotions, and problem-solving behaviors in a game-based learning environment. *Computers & Education*, 147, 103781. <https://doi.org/10.1016/j.compedu.2019.103781>
- Tonguç, G., & Ozkara, B. O. (2020). Automatic recognition of student emotions from facial expressions during a lecture. *Computers & Education*, 148, 103797. <https://doi.org/10.1016/j.compedu.2019.103797>
- Uçar, H. (2017). Açık ve uzaktan öğrenmede motivasyon tasarımı [Motivation design in open and distance learning]. V. Yüzer (Eds.) *Açık ve Uzaktan Öğrenmede Bireysel Farklılıklar [Individual Differences in Open and Distance Learning]* (pp.47-69). Anadolu Üniversitesi Açıköğretim Fakültesi Yayını.
- Wang, W., Xu, K., Niu, H., & Miao, X. (2020). [Retracted] Emotion Recognition of Students Based on Facial Expressions in Online Education Based on the Perspective of Computer Simulation. *Complexity*, 2020(1), 4065207. <https://doi.org/10.1155/2020/4065207>
- Yadegaridehkordi, E., Noor, N. F. B. M., Ayub, M. N. B., Affal, H. B., & Hussin, N. B. (2019). Affective computing in education: A systematic review and future research. *Computers & Education*, 142, 103649. <https://doi.org/10.1016/j.compedu.2019.103649>
- Yolcu, H. H. (2020). Koronavirüs (covid-19) pandemi sürecinde sınıf öğretmeni adaylarının uzaktan eğitim deneyimleri [Distance education experiences of classroom teacher candidates during the coronavirus (covid-19) pandemic]. *Açıköğretim Uygulamaları ve Araştırmaları Dergisi*, 6(4), 237-250. Retrieved from <https://dergipark.org.tr/en/pub/auad/issue/57638/788890>
- Yoshitomi, Y., Kim, S., Kawano, T., & Kilazoe, T. (2000). Effect of sensor fusion for recognition of emotional states using voice, face image and thermal image of face. In *9th IEEE International Workshop on Robot and Human Interactive Communication*, pp. 178-183.
- Yuan, Y., Li, Y., Nie, J., Chao, X., & Li, J. (2024). An individual adaptive ubiquitous learning paradigm: Focusing on the collection and utilization of academic emotions. *Computers in Human Behavior*, 156, 108228. <https://doi.org/10.1016/j.chb.2024.108228>
- Zembylas, M., Theodorou, M., & Pavlakis, A. (2008). The role of emotions in the experience of online learning: Challenges and opportunities. *Educational Media International*, 45(2), 107-117. <https://doi.org/10.1080/09523980802107237>

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