




Effectiveness of artificial intelligence integration in design-based learning on design thinking mindset, creative and reflective thinking skills: An experimental study

Mustafa Saritepeci¹ · Hatice Yildiz Durak¹ 

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Abstract

Integrating Artificial Intelligence (AI) into learning activities is an essential opportunity to develop students' varied thinking skills. On the other hand, design-based learning (DBL) can more effectively foster creative design processes with AI technologies to overcome real-world challenges. In this context, AI-supported DBL activities have a significant potential for teaching and developing thinking skills. However, there is a lack of experimental interventions in the literature examining the effects of integrating AI into learner-centered methods on active engagement and thinking skills. The current study aims to explore the effectiveness of AI integration as a guidance and collaboration tool in a DBL process. In this context, the effect of the experimental application on the participants' design thinking mindset, creative self-efficacy (CSE), and reflective thinking (RT) self-efficacy levels and the relationship between them were examined. The participants used ChatGPT and Midjourney in the digital story development process as part of the experimental treatment. The only difference between the control and experimental groups in the digital storytelling process is the AI applications used in the experimental treatment (ChatGPT and Midjourney). In this quasi-experimental method study, participants were randomly assigned to treatment, an AI integration intervention, at the departmental level. 87 participants (undergraduate students) in the experimental group and 99 (undergraduate students) in the control group. The implementation process lasted five weeks. Partial Least Squares (PLS), Structural Equation Modeling (SEM), and Multi-Group Analysis (MGA) were made according to the measurements made at the T0 point before the experiment and at the T1 point after the experiment. According to the research result, the intervention in both groups contributed to the creative self-efficacy, critical reflection, and reflection development of the participants. On the other hand, the design thinking mindset levels of both groups did not show a significant difference in the comparison of the T0 point and the T1 point.

Extended author information available on the last page of the article

Keywords Artificial intelligence · Design-based learning activities · ChatGPT, Design thinking mindset · Thinking skills · Storytelling

1 Introduction

Developments such as artificial intelligence are followed by theoretical and applied studies on integrating these new technologies into learning processes (Aksu Dünya & Yıldız Durak, 2023; Durak & Onan, 2023). Technological developments change how businesses do (Kandlhofer et al., 2016) and the ways of learning and teaching. Chatbot platforms have components that will profoundly affect learning-teaching processes, including various threats and opportunities (Yıldız Durak, 2023a). Although preparing student homework through such environments is a threat, these environments have essential advantages, such as accessing information in the learning-teaching process and providing integration of favorable aspects with methods that support various student activities and creativity. There is a lack of experimental intervention in the literature examining the effects of the integration of artificial intelligence into learner-centered methods on learner active participation and creativity (Lund & Wang, 2023). In this context, this study includes an experimental intervention to address the shortcomings mentioned in the literature.

Design thinking is a skill teachers should have for the effective use of technology in education (Beckwith, 1988; Tsai & Chai, 2012). Teachers' lack of design thinking skills is defined as one obstacle in technology integration. These barriers are classified in the literature as primary, secondary, and tertiary (Ertmer, 1999; Ertmer et al., 2012; Tsai & Chai, 2012). Primary barriers are related to a lack of infrastructure, training, and support (Snoeyink & Ertmer, 2001). Secondary barriers generally include teachers' affective perceptions (e.g., belief, openness to change, self-confidence, and attitude) toward technology integration (Ertmer et al., 2012; Keengwe et al., 2008). Removing primary and secondary barriers does not guarantee that technology integration will provide meaningful learning (Saritepeci, 2021; Yıldız Durak, 2021). Tsai and Chai (2012) explained this situation with tertiary barriers. The learning process is not static; it is dynamic and constantly changing. Therefore, teachers need to have design thinking skills to transform this variable nature of the learning process (Tsai & Chai, 2012; Yıldız Durak et al., 2023). Overcoming tertiary barriers significantly facilitates the effective use of technology in education. Beckwith's (1988) Educational Technology III perspective, which expresses the most effective form of technology use in education, is a flexible structure to provide learners with more meaningful experiences instead of following a systematic process strictly dependent on instructional design, methods, and techniques in educational environments. The Educational Technology III perspective refers to design-based learning practices.

The dizzying developments that occur with technological innovations in today's business, social, and economic life make our predictions about what kind of job a K12 student will do in the future (Darling-Hammond, 2000; Saritepeci, 2021). In

this case, removing the educational technology III perspective and the tertiary barriers to technology integration is essential. Teachers and pre-service teachers should have the skills to be successful in the coming years, which are uncertain in many ways, and to create opportunities to support these learners. The design-based learning approach has remarkable importance in developing the design-oriented thinking skills of the pre-service teacher. In this context, a structure in which artificial intelligence applications are integrated into the digital storytelling method application processes, one of the most effective applications of the design-based learning approach in learning processes, will support the design-oriented thinking skills of pre-service teachers.

2 Related works

Studies on the use of artificial intelligence in education focus on various areas such as intelligent tutoring system (ITS), (Chen, 2008; Rastegarmoghadam & Ziarati, 2017), personalized learning (Chen & Hsu, 2008; Narciss et al., 2014; Zhou et al., 2018), assessment-feedback (Cope et al., 2021; Muñoz-Merino et al., 2018; Ramnarain-Seetohul et al., 2022; Ramesh & Sanampudi, 2022; Samarakou et al., 2016; Wang et al., 2018), educational data mining (Chen & Chen, 2009; Munir et al., 2022) and adaptive learning (Arroyo et al., 2014; Wauters et al., 2010; Kardan et al., 2015). These studies aim to improve the quality of the learning-teaching process by providing individualized learning experiences and increasing the effectiveness of teaching methods.

The intelligent tutoring system is the most prominent study subject in studies on the use of AI in education (Tang et al., 2021). ITS focuses on using AI to provide learners with personalized and automated feedback and guide them through the learning process. Indeed, there is evidence in the literature that using ITS in various teaching areas can improve learning outcomes. Huang et al. (2016) reported that using ITS in mathematics teaching reduces the gaps between advantaged and disadvantaged learners.

Personalized learning environments, another prominent use of AI in education, aim to provide an experience where the learning process is shaped within the framework of learner characteristics. In addition, supporting the learning of individuals who are disadvantaged in subjects such as learning disabilities is a promising field of study. Indeed, Walkington (2013) noted that personalized learning experience provides more positive and robust learning outcomes. Similarly, Ku et al. (2007) investigated the effect of a personalized learning environment on solving math problems. The study results show that the experimental group learners, especially those with lower-level mathematics knowledge, performed better than the control group.

Assessment and feedback, one of the forms of AI in education, is another area where the number of studies on the COVID-19 epidemic has increased (Ahmad et al., 2022; Hoda et al., 2022). Ahmad et al. (2022) compared artificial intelligence and machine learning techniques for assessment, grading, and feedback and

found that accuracy rates ranged from 71 to 84%. Shermis and Burstein (2016) stated that the automatic essay evaluation system gave similar scores to student work with human evaluators, but the system had difficulties in studies that were different in terms of creativity and structure organization. Accordingly, more development and research should be done to help AI systems produce more effective results in assessment and grading. In another study, AI-supported constructive and personalized feedback on the texts created by learners effectively improved reflective thinking skills (Liu et al., 2023). In the same study, this intervention reduced the cognitive load of the learners in the experimental group and improved self-efficacy and self-regulated learning levels.

The use of AI in educational data mining and machine learning has been increasing in recent years to discover patterns in students' data, such as navigation and interaction in online learning environments, to predict their future performance or to provide a personalized learning experience (Baker et al., 2016; Munir et al., 2022; Rienties et al., 2020). Sandra et al. (2021) conducted a literature review of machine learning algorithms used to predict learner performance and they examined 285 studies published in the IEEE Access and Science Direct databases between 2019–2021. The study results show that the most frequently used machine learning algorithm to predict learner performance is the classification machine learning algorithm, followed by NN, Naïve Bayes, Logistic Regression, SVM, and Decision Tree algorithms.

The main purpose of artificial intelligence studies in the field of AI is to create an independent learning environment by reducing the supervision and control of any pedagogical entity by providing learners with a personalized learning process within the framework of the learner and subject area characteristics (Cui, 2022; Zhe, 2021). To achieve this, system designs for predicting learner behaviors with intelligent systems, providing automatic assessment, feedback, and personalized learning experiences, and intervention studies examining their effectiveness come first. This study develops a different perspective and experiences of the learner's create-to-learn process in collaboration with AI. There are predictions in various studies that AI and collaborative learning processes can support the creativity of learners (Kafai & Burke, 2014; Kandlhofer et al., 2016; Lim & Leinonen, 2021; Marrone et al., 2022). In this regard, Lund and Wang (2023) emphasized that the focus should be on developing creativity and critical thinking skills by enabling learners to use AI applications in any learning task (Fig. 1).

3 Focus of study

This study investigates the effectiveness of artificial intelligence integration (Chat GPT and Midjourney application) as a guidance and collaboration tool in the design-based process integrated into educational environments in a design-based learning

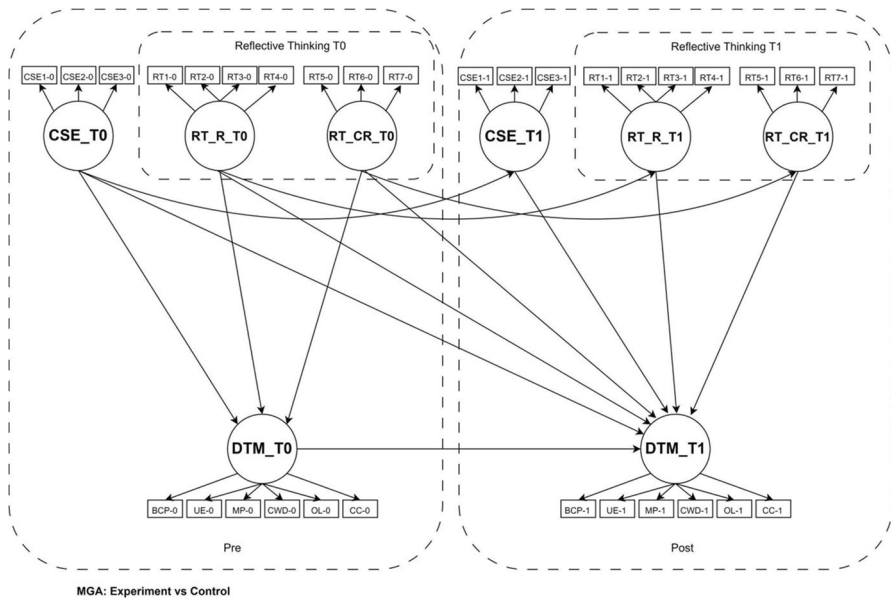


Fig. 1 Proposed structural model. * T0: Time 0 (pretest), T1: Time 1 (posttest). * CSE: Creative self-efficacy, RT_R: Reflective thinking- Reflection, RT_CR: Reflective thinking- Critical reflection, DTM: Design thinking mindset

process. In this context, whether the experimental application was effective in the design thinking mindset levels of the participants and their relationship with creative, reflective thinking self-efficacy was examined.

Participants were tasked with developing a digital story in a design-based process. In the context of experimental treatment, participants were systematically encouraged to use Chat GPT and Midjourney as guidance tools in the digital story development process. Apart from this treatment, the design-based learning process of the control group is very similar to the experimental group.

Therefore, all participants were exposed to the same environment at the university where the application was made, and they did not enroll in any additional technology education courses. This pretest–posttest experimental method study with a control group continued for four weeks, during which the student-produced an active product in design-based learning. In the current research context, the following research questions were addressed:

RQ1: Is the integration of artificial intelligence in a design-based learning process effective on the levels of design thinking mindset, and creative and reflective thinking self-efficacy?

RQ2: Do the relationships between design thinking mindset and creative and reflective thinking self-efficacy levels differ in the context of the experimental process?

In line with these research questions, the following hypotheses were tested:

H1a. Creative self-efficacy for 5 weeks is greater for the experimental group.

H1b. Influence of creative self-efficacy on the design thinking mindset is similar for two groups.

H1c. Influence of creative self-efficacy after 5 weeks on the design thinking mindset is similar for two groups.

H1d. Influence of creative self-efficacy after 5 weeks on the design thinking mindset is greater for the experimental group.

H2a. Influence of critical reflection on the design thinking mindset is similar for two groups.

H2b. Influence of critical reflection on the design thinking mindset after 5 weeks is greater for the experimental group.

H2c. Critical reflection for 5 weeks is greater for the experimental group.

H2d. Influence of critical reflection after 5 weeks on the design thinking mindset is greater for the experimental group.

H3a. Influence of reflection on the design thinking mindset is similar for two groups.

H3b. Influence of reflection on the design thinking mindset after 5 weeks is greater for the experimental group.

H3c. Reflection for 5 weeks is greater for the experimental group.

H3d. Influence of reflection after 5 weeks on the design thinking mindset is greater for the experimental group.

H4. Design thinking mindset for 5 weeks is greater for the experimental group.

4 Methods

4.1 Research design

This study is a quasi-experimental method study with the pretest–posttest control group (Fig. 2). In this experimental methodology study, participants were randomly assigned to treatment, an AI integration intervention, at the departmental level. There were 87 (46.8%) participants in the experimental group and 99 (53.2%) participants in the control group. The participants were pre-service teachers studying in the undergraduate program of the faculty of education.

The treatment in this study also served the purposes of the educational technology course as the application of design-based learning activity as an important tool in educational technology that participants (pre-service teachers) might consider using in their future teaching careers.

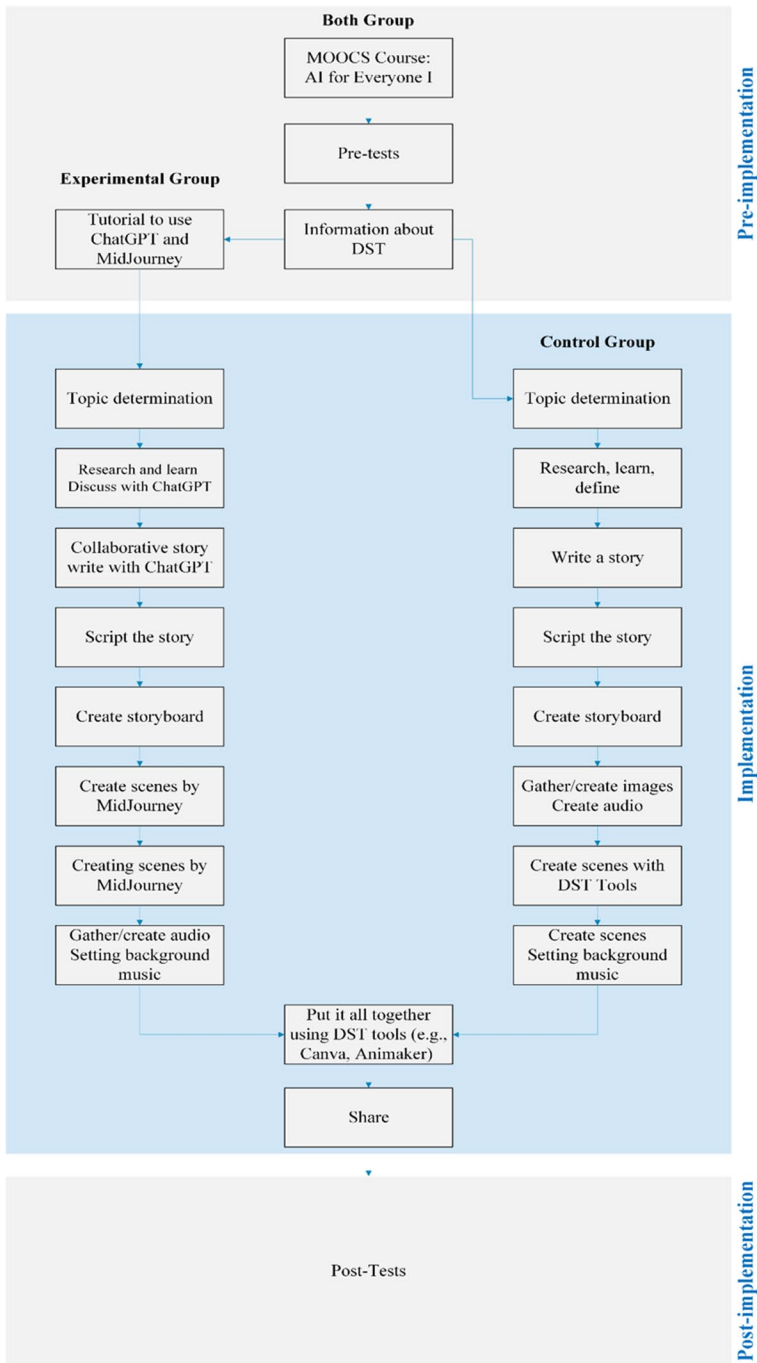


Fig. 2 Implementation Process

In addition, all participants have been exposed to the same opportunities regarding the use of digital technologies in education and none of them attended an additional course. Therefore, the prior knowledge of both groups was similar. Participation in the surveys is completely voluntary. For this reason, although 232 and 260 participants participated in the pretest and posttest, respectively, 186 students who filled in both questionnaires and participated in the application were included in the study. However, both groups were given the same input on design-based learning activities and tasks. Therefore, there is no learning loss for the control group.

4.2 Participants

The participants were 186 pre-service teachers studying at a state university in Turkey. All participants are enrolled in an undergraduate instructional technology course and study in five different departments. The ages of the participants vary between 17–28 years, with an average age of 19.12. 74.2% of the participants were female and 25.8% were male. The high rate of women is because the education faculties in Turkey have a similar demographic structure. The majority of the participants are first-year and second-year students.

The daily use of social technology (social media, etc.) is 3.89 (in hours). Technology usage time for entertainment (watching movies and series, listening to music, etc.) is 2.7 h. While the daily use of technology for gaming (mobile, computer, console games, etc.) is 0.81, the period of use of technology for educational purposes is 1.74. The participants use technology primarily for social and entertainment purposes.

4.3 Procedure

4.3.1 Experimental group

In this group, students performed the DST task as a DBL activity using ChatGPT and MidJourney artificial intelligence applications. These tasks include selecting topics, collaborative story writing with ChatGPT, scripting, creating scripted scenes with MidJourney, and voice acting, as well as integrating them. Examples of multimedia items prepared by the students in this group are shown in Fig. 3.

The artificial intelligence applications they will use in this task were introduced one week before the application. Students did various free activities with these applications. In the first week of the application, students were asked to choose a topic within a specific context. The students researched their chosen topic and chatted with ChatGPT to deepen their knowledge. The students created the stories within the steps of the instruction presented by the instructor in collaboration with ChatGPT. (1) ChatGPT should be asked three questions while creating the story setup. Each question should contribute to the formation of the story. (2) A story should



Fig. 3 Experimental group student products-screenshot

be created by organizing ChatGPT's answers. (3) At least 20% and a maximum of 50% of the story must belong to the student. To assess whether the students executed these three steps accurately and to offer feedback when needed, they shared the link to the page containing their conversations with the questions and answers they used to create their stories with the course instructor. The instructor compared the text accessed from this page with the final text of the student's story. He scanned the final versions of the student stories on Turnitin to check if the student's contribution to the story creation was no more than 50%.

In the next stage (weeks 2 and 3), students created each scene using MidJourney artificial intelligence bots in line with the storyboards they created by scripting their stories. The most important challenge for the students was to ensure continuity in interrelated and successive scenes using MidJourney bots, and they created the audio files by voicing the texts related to each scene. In the fourth week, students combined elements such as scenarios, scenes, and sound recordings using digital story development tools (Canva, Animaker, etc.). The final version of the digital stories was shared on the Google Classroom platform.

Learners sent the product they created for each application step and information about the process from the activity links on the Google Classroom course page. The course instructor reviewed these posts and provided corrective feedback to the students.

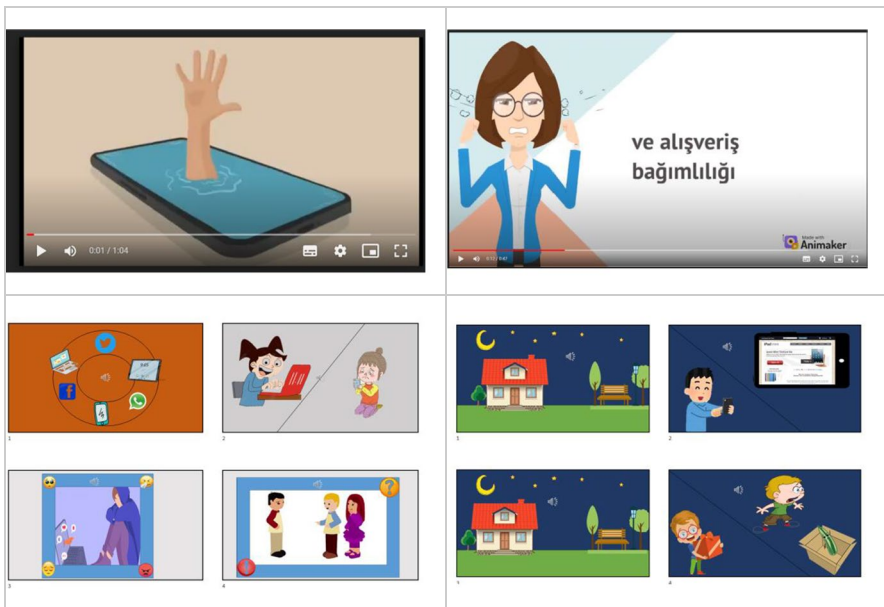


Fig. 4 Control group student products-screenshot

4.3.2 Control group

In this group, students were tasked with preparing a digital story on a topic as DBL activities. This task includes choosing a subject, writing a story, scripting, preparing multimedia elements, and integrating them. Products such as storyboards and videos produced by students in DBL activities carried out in this group are shown in Fig. 4.

In the first week of the application, the participants were asked to choose a topic within a context, as in the experimental group. The students researched the determined topic, created a story related to the subject, then scripted the story and prepared the storyboards. In the second and third weeks of the application, the students created the audio files by vocalizing the texts related to each scene (according to the scenario) in line with the storyboard. Furthermore, pictures, backgrounds, and characters were created in line with the scenario (usually compiled from ready-made pictures and characters). In the fourth week, digital story development tools combined scenarios, pictures, backgrounds, sound recordings, and characters. The final version of the stories was shared on the Google Classroom platform.

4.4 Data collection and analysis

Data were collected at two-time points via the online form. Personal Information Form and three different data collection tools were used in this study.

4.4.1 Instrumentation

Self-description Form There are 8 questions in the personal information form. These were created to collect information about gender, age, department, class, and total hours spent using digital technologies for different purposes.

Design Thinking Mindset Scale The scale was developed by Ladachart et al. (2021) and consists of six sub-dimensions: being comfortable with problems, user empathy, mindfulness of the process, collaborative working with diversity, orientation to learning, and creative confidence. The rating is in a 5-point Likert type. The validity and reliability values of the scale are presented in Sect. 5.

Reflective Thinking Scale Kember et al. (2000) developed this scale to measure students' belief in their ability to be creative; the Turkish adaptation of this scale was created by Başol and Evin Gencil (2013). Although the scale consists of four sub-dimensions, two were included in the study because they were suitable for the study, and the rating is in a 5-point Likert type. The validity and reliability values of the scale are presented in Sect. 5.

Creative Self-Efficacy Scale The original scale, developed by Tierney and Farmer (2011) to measure their belief in their ability to be creative, was adapted into Turkish by Atabek (2020). The scale consists of three items, and the rating is a 7-point Likert type. In the context of this study, the data before the analysis was converted into a 5-point Likert structure, and the validity and reliability values of the scale are presented in Sect. 5.

4.4.2 Analysis

The effect of design-based learning activities integrated with artificial intelligence as a teaching intervention was tried to be measured by repeated measurement. Data collection tools were applied in the first week (T0) and the fifth week (T1) in the experimental and control groups. For analysis, only the responses (survey data) provided by students who fully participated in the application and answered the data collection tools at both T0 and T1 points were included. Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used to analyze the data and test the hypotheses. SmartPLS 4 was used in the analysis (Ringle et al., 2022). The PLS-SEM method allowed the parameters of complex models to be estimated without making any distribution assumptions on the data. In addition, the differences between the experimental and control groups were examined using the Multiple Group Analysis (MGA) features in PLS-SEM, and it was tested whether there was a significant difference between MGA and group-specific external loads and path coefficients.

5 Results

In the first stage, the measurement model was tested. In the second stage, the structural model was evaluated in the context of MGA.

Table 1 Reliability values: Cronbach's alpha, Composite reliability rho_a, and AVE

	Cronbach's alpha	Composite reliability (rho_a)	The average variance extracted (AVE)
Creative Self-efficacy T0	0.785	0.792	0.702
Creative Self-efficacy T1	0.815	0.822	0.730
Design Thinking Mindset T0	0.796	0.869	0.514
Design Thinking Mindset T1	0.861	0.887	0.6
Critical Reflection T0	0.755	0.754	0.672
Critical Reflection T1	0.746	0.760	0.7
Reflection T0	0.845	0.858	0.7
Reflection T1	0.859	0.865	0.703

Table 2 Discriminant validity: Heterotrait-monotrait ratio (HTMT)

	Creative Self- efficacy T0	Creative Self- efficacy T1	Design Thinking Mindset T0	Design Thinking Mindset T1	Critical Reflection T0	Critical Reflection T1
Creative Self- efficacy T0	0.601					
Creative Self- efficacy T1	0.779	0.420				
Design Thinking Mindset T0	0.381	0.484	0.481			
Design Thinking Mindset T1	0.450	0.089	0.526	0.263		
Critical Reflection T0	0.446	0.428	0.399	0.511	0.409	
Critical Reflection T1	0.739	0.375	0.817	0.403	0.566	0.358
Reflection T0	0.530	0.680	0.497	0.686	0.197	0.648
Reflection T1						0.539

Table 3 Discriminant validity: Fornell-Larcker criterion

	Creative Self- efficacy T0	Creative Self- efficacy T1	Design Thinking Mindset T0	Design Thinking Mindset T1	Critical Reflection T0	Critical Reflection T1	Reflection T0	Reflection T1
Creative Self-efficacy T0	0.838							
Creative Self-efficacy T1	0.485	0.855						
Design Thinking Mindset T0	0.653	0.365	0.717					
Design Thinking Mindset T1	0.325	0.421	0.408	0.772				
Critical Reflection T0	0.345	0.025	0.434	0.220	0.820			
Critical Reflection T1	0.352	0.341	0.313	0.417	0.307	0.813		
Reflection T0	0.611	0.317	0.733	0.366	0.449	0.299	0.826	
Reflection T1	0.436	0.571	0.431	0.608	0.150	0.535	0.469	0.839

5.1 Measurement model

When the measurement and structural models were evaluated, the indicator loads were higher than the recommended value of 0.7 (See Appendix Table 7).

Internal consistency reliability is represented by Cronbach's alpha, composite reliability (CR), and rho_a (See Table 1). All values are above the threshold value of 0.70 by default. For convergent validity, the average variance extracted (AVE) value is used and this value is expected to be above 0.5. The values in the model were found to be higher than this threshold value.

Heterotrait-monotrait ratio (HTMT) and the Fornell-Larcker criterion were used for discriminant validity. The values found indicate that discriminant validity has been achieved, as seen in Tables 2 and 3.

Considering all the data obtained, the measurement model of the proposed model is suitable for testing hypotheses.

5.2 SEM

The structural model of the PLS-SEM was examined as it provides the measurement model assumptions. PLS-SEM was run using 1000 bootstrapping. The significant differences in the path coefficients of the assumed relationships between design thinking mindset levels and creative and reflective thinking self-efficacy between the experimental and control groups were examined, and the findings are presented in Table 4.

According to Table 4, the structural model was examined in terms of significant differences in the path coefficients of the assumed relationships to test the research hypotheses, and the creative self-efficacy and reflective thinking dimensions for the students in the experimental and control groups differed after the treatment process.

R² values indicate the explanatory power of the structural model and these values show moderate to significant power (See Table 5).

To examine whether there is a significant difference between the path coefficients for the experimental and control groups, the PLS-MGA Parametric test values were examined and the results are presented in Table 6.

According to Table 6, the findings show that there is no significant difference in the effect of creative self-efficacy, and reflective thinking on design thinking mindset between the two groups. After the treatment process, there is no significant difference in the relationships between creative self-efficacy, reflective thinking, and design thinking mindset. The significance levels of the path coefficients showed that the hypotheses were not supported.

6 Discussion and conclusion

This study examined the effect of AI integration, which is integrated into the digital storytelling process, a design-based learning method, on design thinking mindset and whether it is effective in its relations with creative, reflective thinking

Table 4 Multi Group Analysis (MGA) Path coefficients

Hypotheses	Path	Experiment group			Control group		
		Path coefficients	t value	p	Path coefficients	t value	P
H1a	Creative Self-efficacy T0 → Creative Self-efficacy T1	0.490	5.586	0.000	0.522	6.092	0.000
H1b	Creative Self-efficacy T0 → Design Thinking Mindset T0	0.393	4.901	0.000	0.225	3.402	0.001
H1c	Creative Self-efficacy T0 → Design Thinking Mindset T1	-0.015	0.144	0.886	-0.002	0.011	0.991
H1d	Creative Self-efficacy T1 → Design Thinking Mindset T1	0.041	0.344	0.731	0.201	1.633	0.103
H2a	Critical Reflection T0 → Design Thinking Mindset T0	0.076	0.765	0.445	0.121	1.864	0.062
H2b	Critical Reflection T0 → Design Thinking Mindset T1	0.093	0.706	0.480	0.172	2.137	0.033
H2c	Critical Reflection T0 → Critical Reflection T1	0.308	2.802	0.005	0.363	3.871	0.000
H2d	Critical Reflection T1 → Design Thinking Mindset T1	0.062	0.420	0.675	0.113	1.213	0.225
H3a	Reflection T0 → Design Thinking Mindset T0	0.434	5.493	0.000	0.559	6.697	0.000
H3b	Reflection T0 → Design Thinking Mindset T1	0.427	4.169	0.000	0.273	1.877	0.061
H3c	Reflection T0 → Reflection T1	0.517	5.296	0.000	0.475	4.732	0.000
H3d	Reflection T1 → Design Thinking Mindset T1	0.399	2.778	0.006	0.452	3.755	0.000
H4	Design Thinking Mindset T0 → Design Thinking Mindset T1	0.247	1.715	0.086	0.107	0.836	0.403

Table 5 R2 values

	R-square	R-square adjusted
Creative Self-efficacy T1	0.235	0.231
Design Thinking Mindset T0	0.613	0.606
Design Thinking Mindset T1	0.417	0.394
Critical Reflection T1	0.094	0.090
Reflection T1	0.220	0.215

self-efficacy. The participants used ChatGPT and Midjourney applications in the digital story development process as part of the experimental treatment. The only difference in the digital storytelling process between the control and experimental groups is the AI applications used in the experimental treatment. The experimental intervention covers four weeks. Data were collected from the participants before (T0) and after the application (T1) with data collection tools. There is a significant difference at the T1 point compared to the T0 point in both groups' creative self-efficacy, critical reflection, and reflection levels. Accordingly, the intervention in both groups contributed to the participants' creative self-efficacy, critical reflection, and reflection development. On the other hand, the design thinking mindset levels of both groups did not show a significant difference in the comparison of the T0 point and the T1 point.

According to the multigroup comparison of the creative self-efficacy level at T0 and T1 points, there was no significant difference between the groups. When compared to T0 at the T1 point, creative self-efficacy improvement was achieved in both groups. This is valuable as it shows that the creative self-efficacy contribution of intensive use of AI support in a design-based learning environment is similar. Indeed, creativity, recognized as one of the core competencies in education, is part of CSE, which includes the belief that an individual is capable of producing creative results (Yildiz Durak, 2023b). There are predictions in various studies that AI and collaborative learning processes can support the creativity of learners (Kafai & Burke, 2014; Kandlhofer et al., 2016; Lim & Leinonen, 2021; Marrone et al., 2022). Marrone et al. (2022) provided eight-week training sessions on creativity and AI to middle school students. In their subsequent interviews with the students, the most dominant opinion was that AI support had a crucial role in supporting their creativity. In support of this, the experimental treatment in our study requires various creative interventions from the students: (1) Students asked at least three questions to ChatGPT while creating a story. (2) Each question contained abstracting from the previous AI answer and directions on how to continue. (3) they also created their constructs by creating connecting sentences and paragraphs to gather the answers given by ChatGPT. In addition, the second part where creativity came into play was creating scenes related to the story in the Midjourney environment. (4) While creating these scenes, the student

Table 6 Hypotheses test results

Hypotheses	Path Coefficients	Path Coefficient difference (Experiment—Control)	p-value (Experiment Vs Control)	Accept (+) /reject (-) hypotheses
H1a	Creative Self-efficacy T0 is → Creative Self-efficacy T1	-0.032	0.795	-
H1b	Creative Self-efficacy T0 → Design Thinking Mindset T0	0.168	0.109	-
H1c	Creative Self-efficacy T0 → Design Thinking Mindset T1	-0.014	0.931	-
H1d	Creative Self-efficacy T1 → Design Thinking Mindset T1	-0.161	0.345	-
H2a	Critical Reflection T0 → Design Thinking Mindset T0	-0.045	0.728	-
H2b	Critical Reflection T0 → Design Thinking Mindset T1	-0.078	0.624	-
H2c	Critical Reflection T0 → Critical Reflection T1	-0.055	0.703	-
H2d	Critical Reflection T1 → Design Thinking Mindset T1	-0.051	0.766	-
H3a	Reflection T0 → Design Thinking Mindset T0	-0.125	0.279	-
H3b	Reflection T0 → Design Thinking Mindset T1	0.154	0.383	-
H3c	Reflection T0 → Reflection T1	0.042	0.763	-
H3d	Reflection T1 → Design Thinking Mindset T1	-0.053	0.795	-
H4	Design Thinking Mindset T0 → Design Thinking Mindset T1	0.140	0.457	-

had to plan scenes by abstracting the story he had created in collaboration with AI, create those scenes, and provide detailed parameters to the Midjourney bot to ensure continuity between the scenes. It may be that, relatively, in the expectation control group, the realization of this whole process by the students through various creative practices will further support creativity and self-efficacy. Regarding this situation, Riedl and O'Neill (2009) highlighted that although these tools (Canva, Animaker, etc.) make it possible to develop creative content, the user may not get significant results. In this context, they pose an essential question: "Can an intelligent system augment non-expert creative ability?". Lim and Leinonen (2021) argued that AI-powered structures can effectively support creativity and that humans and machines can learn from each other to produce original works. Taking this one step further, AI will contribute to students' creativity in learning and teaching processes (Kafai & Burke, 2014). Indeed, Wang et al. (2023) found a significant relationship between students' AI capability levels and their creativity, explaining 28.4% of the variance in creativity.

According to the research findings, all ways between reflective thinking scale sub-dimensions critical reflection and reflection and design thinking mindset are insignificant (H2a, H2b, H2d, H3a, H3b, H3d). In addition, there is no significant difference between the groups according to the multi-group comparison at T0—T1 points for reflection and critical reflection. On the other hand, there is a significant improvement in the critical reflection and reflection levels at the T1 point of both groups compared to the T0 point. Accordingly, AI collaboration has a similar effect to the process in the control group on the learners' reflective thinking levels in the design-based learning process. In support of this, we have evidence that incorporating AI in various forms in educational processes has essential outcomes for reflective thinking. Indeed, Liu et al. (2023) reported that an intervention involving incorporating AI into the learning process as a feedback tool to support reflective thinking in foreign language teaching resulted in remarkable improvements in learning outcomes and student self-efficacy.

DBL involves learners assimilating new learning content to overcome authentic problems and creating innovative products and designs to showcase this learning in the simplest way possible. In this study, DST processes, which allow the application of DBL to different learning areas, are included in both interventions. In the literature, DST helps learners reflect on what they have learned (Ivala et al., 2014; Jenkins & Lonsdale, 2007; Nam, 2017; Robin, 2016; Sandars and Murray, 2011) and develop reflective thinking skills (Durak, 2018; Durak, 2020; Malita & Martin, 2010; Sadiq, 2008; Saritepeci, 2017) is a method with critical elements. The critical implication here is that all processes of AI collaboration on reflection and critical reflection have a similar effect as the DST process planned by the learners. The similar effect of AI collaboration allowed learners to understand the benefits of AI in the DST process and to develop in-depth learning by combining their thought processes with AI and finding creative ways to reflect on their learning. Indeed, Shum and Lucas (2020) claims that AI can help individuals think more deeply about

challenging experiences. The DST process includes stages (story writing, scenario creation, planning scenes, etc.) that allow learners to embody their reflections on their learning (Ohler, 2006; Saritepeci, 2017).

The multi-group analysis results of the road between the design thinking mindset T0 – T1 points are insignificant (H4). In addition, there was no significant improvement in design thinking mindset scores in both groups compared to T0 at the T1 point. Accordingly, the effect of the design-based learning process carried out in the experimental and control groups on the learners' design thinking mindset scores was limited. The study's expectation was the development of the design thinking levels of the learners and, as a result, meaningful improvements in the design thinking mindset levels. This result may be because the application process is not long enough to develop versatile skills such as design thinking. Raz-zouk and Shute (2012) emphasized that design thinking is challenging to acquire in a limited context. However, they argue that students can learn to design thinking skills together with scaffolding, feedback, and sufficient practice opportunities. The DST process included scaffolding and feedback processes in both groups. Although there are different stages for acquiring and developing design thinking skills during the application process, the similar characteristics of the design thinking mindset level may indicate the need for more extended practice. However, the fact that the design thinking mindset is a self-reporting tool limits our predictions about individuals' design thinking skill acquisition and development in the process.

7 Conclusion

In conclusion, the intensive use of AI support in a design-based learning environment similarly impacts the development of participants' creative self-efficacy, reflective thinking, and design thinking mindset levels. The AI collaboration process showed a similar effect to the planned design-based learning process by allowing learners to understand the benefits of AI in the design thinking mindset and to develop in-depth learning by combining their thought processes with AI. However, it is essential to note that the study's expectation of meaningful improvements in the design thinking mindset levels was unmet. This suggests that more extended practice periods and more support and feedback processes may be necessary to effectively develop versatile skills such as design thinking.

The research contributes to our understanding of the impact of AI collaboration on learners' levels of creative self-efficacy, reflective thinking, and design thinking mindset. Further studies with extended practice periods and additional scaffolding and feedback processes could provide valuable insights into the effective development of design thinking skills in AI-supported design-based learning environments.

Appendix

Table 7 Measurement model values

Items no	Constructs/ items	Experiment (N = 87)		Control (N = 99)		Loading (T0) Loading (T1)	
		T0	T1	T0	T1	Mean	SD
		Mean	SD	Mean	SD	Mean	SD
	Reflective Thinking						
<i>RT_R</i>	Reflection						
RT1	Sometimes I question the way others do something and try to think of a better way	4.05	3.79	3.57	3.71	1.052	0.865
		0.776	0.904	1.061			0.806
RT2	I like to think about what I'm doing and consider alternative ways of doing it	4	3.79	3.66	3.89	0.936	0.858
		0.682	1.091	0.939			0.890
RT3	I often reflect on my actions to see if I can improve what I do	4.06	3.87	3.79	3.85	0.861	0.804
		0.854	0.95	0.929			0.833

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)		Control (N = 99)		Loading (T0) Loading (T1)					
		T0		T0		T1					
		Mean	SD	Mean	SD	Mean	SD				
RT4	I often review my achievements so that I can learn from my experiences and improve my further practice	3.82	0.922	3.63	1.024	3.62	0.966	3.78	0.887	0.775	0.823
RT_CR	Critical Reflection										
RT5	As a result of this course, I changed the way I look at myself	3.55	0.949	3.64	1.034	3.38	1.076	3.66	0.917	0.785	0.829
RT6	This course has shaken/questioned some of the ideas that I hold very tightly	3.06	1.071	3.25	1.164	3.07	1.154	3.51	1.082	0.862	0.838

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
RT7	During this course, I discovered that there are errors in what I previously believed to be true	3.57	1.03	3.51	1.14	3.19	1.094	3.68	0.935	0.811	0.770
CSE	Creative Self-efficacy										
CSE1	I think I am good at generating original ideas	3.59	0.983	3.47	1.098	3.55	1.052	3.62	0.955	0.856	0.880
CSE2	I am confident in my ability to solve problems creatively	3.52	0.913	3.53	1.01	3.45	1.013	3.63	0.985	0.898	0.883

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
CSE3	I am skilled at further developing the ideas of others	3.54	0.938	3.52	0.951	3.55	1.023	3.6	0.936	0.754	0.798
DTM	Design Thinking Mindset										
BCP	Being comfortable with problems	8.1609	2.32716	8.7816	2.71698	9.0909	2.7961	9.5152	2.85129	0.436	0.7
DT1	I feel comfortable even when dealing with unresolved problems	2.59	1.04	2.84	1.15	2.88	1.163	2.96	1.142		
DT2	I like when a problem solution is unexpected	3.1	1.249	3.21	1.173	3.35	1.272	3.54	1.109		

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
DT3	I don't worry even when I'm looking for a solution to a problem that I don't know if it's a successful (good) problem	2.47	1.055	2.74	1.094	2.86	1.079	3.02	1.106		
UE	User empathy	11.1264	2.18241	10.8736	2.33181	10.596	2.49865	10.9798	2.47015	0.4	0.6
DT4	During the design process, I try to understand the needs of users (people who watch the content you have prepared, etc.)	4.09	0.816	3.69	0.931	3.59	1.02	3.74	1.036		

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
DT5	In the design process, I often see the problem from the users' point of view	3.23	0.985	3.51	1.01	3.32	1.028	3.55	1.023		
DT6	In the design process, I usually put myself in the users' shoes	3.8	0.887	3.68	0.909	3.69	0.976	3.7	0.942		
MP	Mindfulness of the process	11.0805	2.29873	10.3678	2.47835	10.3636	2.50491	10.7374	2.83414	0.867	0.842
DT7	I am aware of when to open my mind and when to focus on something	3.84	0.913	3.59	1.063	3.55	0.982	3.59	1.116		

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
DT8	I believe in focusing on discovering new things rather than worrying about unsuccessful results	3.61	1.165	3.39	1.038	3.43	1.153	3.64	1.12		
DT9	I am aware of when I need to redefine any problem more clearly	3.63	0.954	3.39	0.944	3.38	1.037	3.52	1.024		
CWD	Collaborative working with diversity	9.4023	2.63456	9.2069	2.8698	8.9697	2.74217	10.0202	2.77003	0.800	0.843
DT10	I prefer to work in a group rather than alone	3.06	1.175	3.03	1.224	3.07	1.288	3.43	1.171		

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
DT11	I love working with different people	3.49	1.209	3.26	1.298	3.11	1.186	3.47	1.164		
DT12	In group work, I accept the group's decisions even if I disagree with them	2.85	1.225	2.91	1.207	2.79	1.052	3.11	1.077		
OL	Orientation to learning	28.2184	4.06753	26.092	5.3649	25.9192	5.50079	26.4343	5.70385	0.879	0.876
DT13	I often apply what I have learned	3.43	0.923	3.29	0.987	3.34	0.949	3.61	0.913		
DT14	I love to learn from experiences, observations, and actions	4.3	0.749	3.97	0.958	3.74	0.975	3.91	0.98		

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
DT15	I like to learn with my friends in and between groups	3.9	1.012	3.69	1.124	3.62	1.085	3.71	1.1		
DT16	I love to learn from people with different and diverse perspectives	4.41	0.786	3.89	0.982	3.84	1.167	3.83	0.99		
DT17	I love receiving feedback and learning from it	4.16	0.805	3.87	0.887	3.9	0.931	3.78	0.898		
DT18	I'm trying to get information that I don't know at all	3.92	0.905	3.66	1.087	3.77	1.008	3.78	1.065		
DT19	I can discuss, share and learn from mistakes	4.1	0.793	3.74	0.982	3.72	1.04	3.83	0.926		

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)				Control (N = 99)				Loading (T0) Loading (T1)	
		T0		T1		T0		T1		Mean	SD
		Mean	SD	Mean	SD	Mean	SD	Mean	SD		
CC	Creative confidence	18.7241	3.59486	17.931	4.06572	18.2525	4.55431	18.6768	4.21811	0.756	0.783
DT20	I can make inferences and suggest ideas based on missing information	3.69	0.931	3.72	0.985	3.58	1.098	3.61	1.038		
DT21	I like to use creative thinking to solve complex problems	3.91	0.858	3.61	0.992	3.64	1.138	3.77	1.048		
DT22	I like to think of new things different from the existing ones	3.9	0.915	3.59	1.04	3.73	1.038	3.76	1.001		
DT23	I like to create a model to represent a new idea	3.6	1.017	3.51	1.066	3.63	1.006	3.78	0.975		

Table 7 (continued)

Items no	Constructs/ items	Experiment (N = 87)		Control (N = 99)		Loading (T0) Loading (T1)			
		T0		T1		T1			
		Mean	SD	Mean	SD	Mean	SD		
DT24	I like to create new conditions to test other possibilities	3.63	0.99	3.51	1.033	3.69	1.085	3.77	0.988

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Declarations

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Ethical statement The research was conducted in a school in Turkey and approved by the school administration. Participation was voluntary and anonymous. Informed consent was obtained from all participants.

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Authors and Affiliations

Mustafa Saritepeci¹ · Hatice Yildiz Durak¹ 

✉ Hatice Yildiz Durak
hatyil05@gmail.com

Mustafa Saritepeci
mustafasaritepeci@gmail.com

¹ Eregli Faculty of Education, Department of Educational Sciences, Necmettin Erbakan University, Konya, Turkey