Relating Creative Self-Efficacy and Cognitive Load Development in Adolescents Engaged in an AI-Supported Environment

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Summary

Creativity is an essential 21st century skill that should be fostered in education to prepare children for their future careers. Several studies indicate the positive influence of creative self-efficacy (CSE) on creativity. Recent research highlights that AI-supported learning environments have the potential to heighten CSE through scaffolding, for example by offering students successful learning experiences and gradually withdrawing support. Moreover, these environments could mitigate cognitive load (CL) – the mental effort required to process information –, a concept that is positively related to CSE. This study investigated how CSE develops and relates to CL in 13 male Australian secondary school students engaging in a three-week AI-supported learning programme. Participants worked in small groups to build a Mars Rover, receiving scaffolded support from an AI-based vision analytics tool that uses algorithms to interpret and analyse visual information. Data were collected through repeated self-report measures and analysed using descriptive statistics, Pearson correlations, and Generalized Estimating Equations (GEE). Results showed a significant increase in CSE across sessions. While CSE was positively associated with CL – in contrary to previous research – this relationship weakened over time. This study contributes to the growing body of literature on AI-supported learning by demonstrating that scaffolded AI tools can promote CSE in adolescents over a short period of time. Moreover, these findings offer promising directions for future research and educational practice. Learning environments similar to the one used in this study, for example, could be integrated into broader curricula and over extended periods of time to foster students' CSE.

Keywords: creative self-efficacy, cognitive load, AI-supported learning evnvironment, scaffolding, vision analytics, secondary education

Samenvatting

Creativiteit moet in het onderwijs gestimuleerd worden om kinderen voor te bereiden op hun toekomstige carrière. Verschillende studies tonen de positieve invloed van *creative self-efficacy* (CSE) op creativiteit. Volgens recent onderzoek bieden AI-ondersteunde leeromgevingen kansen om CSE te vergroten met *scaffolding*, bijvoorbeeld door succeservaringen te creëren en ondersteuning geleidelijk af te bouwen. Daarnaast kunnen deze omgevingen helpen *cognitive load* (CL) – de mentale inspanning die nodig is om informatie te verwerken – te reguleren. Ander onderzoek suggereert bovendien een positieve relatie tussen CL en CSE. In deze studie is onderzocht hoe CSE zich ontwikkelt in relatie tot CL bij dertien Australische mannelijke middelbare scholieren (14-16 jaar) tijdens een drie weken durend lesprogramma. De leerlingen werkten in kleine teams aan het bouwen van een Mars Rover, ondersteund door een AI-*vision analytics tool* die visuele data analyseert via algoritmes. Data werden verzameld via herhaalde zelfrapportages en geanalyseerd met beschrijvende statistiek, Pearson-correlaties en Generalized Estimating Equations (GEE). De resultaten laten een significante toename van CSE gedurende de sessies zien. Hoewel CSE positief samenhing met CL, werd deze relatie gaandeweg zwakker – in contrast met eerdere bevindingen. Deze studie draagt bij aan de groeiende kennis over AI-ondersteunde leeromgevingen, door te laten zien dat deze CSE op korte termijn kunnen versterken door middel van *scaffolding*. Bovendien biedt de studie waardevolle inzichten voor verder onderzoek en voor de onderwijspraktijk. Leeromgevingen vergelijkbaar aan de leeromgeving gebruikt in deze studie, kunnen bijvoorbeeld worden geïntegreerd in bredere curricula voor langere periodes om CSE onder studenten te stimuleren.

Trefwoorden: creative self-efficacy, cognitive load, AI-ondersteunde leeromgeving, scaffolding, vision analytics, voortgezet onderwijs

Introduction

Most children entering school today will eventually work in jobs that do not yet exist. Creativity is a crucial 21st century skill that must be fostered in education to prepare children for these future careers, where they need to tackle unstructured problems, handle new information, and carry out non-routine tasks (WEF, 2016). An increasing number of countries recognize that creativity is a key skill that needs to be developed in education. It is no longer seen as an optional addition to curricula, but as a fundamental skill that should be integrated in all subjects (Patston et al., 2021). Secondary school students are particularly receptive to creativity training, as adolescence is a critical time for creative development (Barbot & Heuser, 2017). This heightened potential is linked to increased neural activity in brain regions associated with creative thinking (Kleibeuker et al., 2023). Moreover, adolescents demonstrate greater improvements in originality compared to adults when participating in creativity training, suggesting heightened sensitivity to creative interventions (Stevenson et al., 2014).

Despite their great potential to improve their creative abilities, research shows a decline in creativity among adolescents (Gralewski et al., 2016). This "adolescent slump" in creativity is paralleled by a drop in creative self-efficacy (CSE) that follows a similar pattern (Karwowski, 2015). According to self-efficacy theory (Bandura, 1982) one's belief in their own capabilities is a crucial predictor of outcomes. Hence, it is not unexpected that the moment CSE drops during adolescence, the outcome, in this case creativity, also drops. Accordingly, several studies indicate that higher levels of CSE can positively influence creativity (e.g., Herianto et al., 2024; Tierney & Farmer, 2011; Wang et al., 2024). To effectively boost CSE, learners need to experience success in developing new skills – an essential mechanism for growing confidence (Bandura, 1982).

These success experiences can be structured using Vygotsky's zone of proximal development (ZPD), which identifies the space between what a learner can do independently and what they can achieve with guidance (Vygotsky, 1978). This guidance, commonly referred to as scaffolding, entails the management of complex task elements so learners can focus on achievable components (Wood et al., 1976). In doing so, scaffolding helps regulate cognitive load (CL) – the mental effort required to process new information, limited by working memory capacity (Sweller, 1988; Sweller et al., 2019). Since lower CL is associated with higher CSE (Redifer et al., 2021), managing CL may be a promising pathway to enhance creative self-efficacy in adolescents. Moreover, as learners gain competence and their ZPD shifts, support is gradually withdrawn. Shifting responsibility for learning from tutor to learner acknowledges student mastery, which also contributes to the development of self-efficacy (Walker, 2010).

In recent years, educational technologies using AI algorithms have become more common in the classroom (Gabriel et al., 2022). While concerns arise that excessive reliance on AI may inhibit students' creativity (Boers et al., 2025; Raimi et al., 2024), research has also highlighted AI's potential to enhance this skill by enabling students to experiment with problem-solving techniques and to adapt their approaches as necessary (Liu, 2023). Accordingly, students have indicated that AI might enhance their creativity by promoting independent thinking and providing opportunities for creative expression (Marrone et al., 2022). AI-supported learning environments can offer scaffolded support through interactive prompts, feedback, simulations, instructional guides, and digital assistants that guide students through complex tasks, for example by sending messages to encourage effort and persistence (Triana-Vera & López-Vargas, 2025). Accordingly, the purpose of the current study is to explore how CSE develops in adolescents engaging with an AI-supported learning environment providing scaffolded support, and therefore managing CL. By examining not only how CSE changes over time, but also how this relates to CL, this study aims to contribute to the understanding of AI's potential to mitigate the "adolescent slump" in CSE.

The "adolescent slump" in creative self-efficacy

Creative self-efficacy (CSE) is a combination of two concepts: creativity and self-efficacy. Creativity is commonly defined as generating ideas that are useful and did not already exist in the same form (Runco & Jaeger, 2012). Self-efficacy refers to individuals' beliefs about their abilities to succeed at domain-specific tasks. These beliefs, whether accurate or not, both influence which activities people will take on and how much effort and time they will expend when they face obstacles along the way (Bandura, 1982). CSE increases everyday creativity in adolescents, because individuals with higher CSE believe that they are creative, show more self-motivation and are more persistent (Wang et al., 2024). Unsurprisingly, the development of creativity and CSE follow similar trajectories: both tend to increase through childhood, followed by a temporary decline during adolescence that starts around age 14. After this dip, CSE and creativity rise again, peaking around age 20 (Gralewski et al., 2016; Karwowski, 2015).

Relating cognitive load to creative self-efficacy

Students with higher levels of CSE are likely to report lower levels of CL, because they tend to perceive tasks as less complex (Redifer et al., 2021). This relationship can be understood by recognizing that both CL and CSE are perception-based constructs, reflecting, respectively, one's perceived task complexity and belief in one's creative ability. As such, students who have greater confidence in their creative capabilities are more inclined to view creative tasks as manageable, resulting in a reduced CL (Redifer et al., 2021). The concept of cognitive load (CL) comes from cognitive load theory, which describes how the mental demands of a learning task can affect the learner's ability to process new information and build knowledge in long-term memory (Sweller et al., 2019). This theory distinguishes between three types of CL: extraneous, intrinsic, and germane load. Extraneous load does not contribute to learning, as it primarily depends on the instruction design. Intrinsic load, however, is determined by the interaction between task complexity and the learner's expertise. While a task requires high levels of mental effort from one learner, this task may pose less intrinsic load for a more experienced learner. Germane load, lastly, directly supports learning. It refers to the cognitive effort invested in the integration of new information with existing knowledge (van Merriënboer et al., 2006; Sweller, 1988; Sweller et al., 2019). Effective instructional design aims to reduce extraneous load while optimizing germane processing within the learner's cognitive capacity. Concurrently, it manages intrinsic load by tailoring learning tasks to the learner's current skill level. As learners become more advanced, instructional support should gradually diminish, because unnecessary guidance can contribute to extraneous load (van Merriënboer et al., 2006). To foster germane processing, learning tasks should vary, so learners can compare different tasks (Sweller et al., 2019).

Exploring AI's scaffolding possibilities

AI-supported scaffolding has the potential to address all three types of CL, while also fostering the development of CSE. This study explored the use of an AI-based vision analytics tool that interprets and analyses visual information in real time. This tool was researched before by Marrone et al. (2022), who found that after using it, secondary school students believed AI could support their creative development by fostering independent thinking and offering opportunities to be creative. The tool provided scaffolded support to student teams (4–5 members) tasked with assembling a Mars Rover using LEGO Mindstorm EV3 kits. By allowing teams to select which Rover unit to assemble first and displaying the relative skill level of each unit (see Appendix A1), the task was broken into manageable components – reducing intrinsic cognitive load and supporting CSE through achievable challenges and early successes (Bandura, 1982; Wood et al., 1976). Additionally, by highlighting necessary parts, identifying pieces to exclude, and indicating correct placement of LEGO components (see Appendix A2), the tool offered step-by-step instructions, further decreasing intrinsic load (Triana-Vera & López-Vargas, 2025). Feedback was only provided when students actively presented their gathered parts or completed units to the tool (see Appendix A3), which minimized extraneous load by avoiding unsolicited assistance. This design also shifted responsibility for learning to the student – an important factor in the development of self-efficacy (Triana-Vera & López-Vargas, 2025; Walker, 2010). Finally, the vision analytics tool fostered germane load by offering students tasks that were both meaningful, because each unit was essential to completing the Mars Rover, and variable, because the units varied in both structure and difficulty. This promotes deeper processing in two ways: first, by encouraging students to develop a holistic understanding of tasks, which can then be transferred to new situations (van Merriënboer et al., 2006); and second, by helping learners identify patterns and connections between various observations and information sources (Garbuio & Lin, 2021). Taken together, the scaffolding properties of the AI-based vision analytics tool could potentially reduce intrinsic and extraneous load, induce germane load, and support creative self-efficacy (CSE).

The current research

The first objective of this study is to investigate how CSE develops among adolescents aged 14 to 16 over a three-week period in an AI-supported learning environment. According to Bandura (1982), self-efficacy increases when learners engage in tasks that are well-matched to their current skill level. AI systems, through their capacity to scaffold learning, may provide this type of adaptive support by aligning task difficulty with learners' abilities. Although recent research has begun to explore the role of AI in fostering CSE, most of this work has focused on students in higher education. For example, research amongst business administration students investigated the effect of highly intelligent AI assistants on students' innovation behaviour, with CSE as a mediator. The AI assistant interacted with participants, using verbal persuasion to convince participants they are able to do a certain task. The results indicated that high-intelligent AI assistants have positive effects on innovation behaviour via CSE (Yin et al., 2024). Likewise, a study with pre-service teachers in a four-week digital storytelling course showed a significant increase in CSE from the beginning to the end of the programme, regardless of whether AI-support is used (Saritepeci & Durak, 2024). Despite these promising findings, little is known about how AI might impact CSE in younger populations. This is a critical gap, particularly because adolescence is a period marked by a documented decline in CSE (Karwowski, 2015). Based on the above arguments, it is expected that CSE increases when adolescent students participate in an AI-supported learning environment. Therefore, the following hypothesis is proposed:

Hypothesis 1: Students' creative self-efficacy will increase during three weeks in an AI-supported learning environment.

The second objective of this study is to examine the relationship between CSE and CL within an AI-supported learning environment. Cognitive load theory suggests that the mental effort required to complete a task can influence how successfully learners process and integrate new material (Sweller et al., 2019). Learners with higher levels of CSE often perceive tasks as more manageable, which may lead to a reduction in CL reported by students (Redifer et al., 2021). To our best knowledge, previous studies have examined neither the development of CL within an AI-supported learning environment, nor the relationship between the development of CSE and CL in this context. Based on the theory above, it is expected that as CSE increases in an AI-supported learning environment, CL decreases. Therefore, the following hypothesis is proposed:

Hypothesis 2: Higher levels of creative self-efficacy are associated with lower cognitive load during three weeks in an AI-supported learning environment.

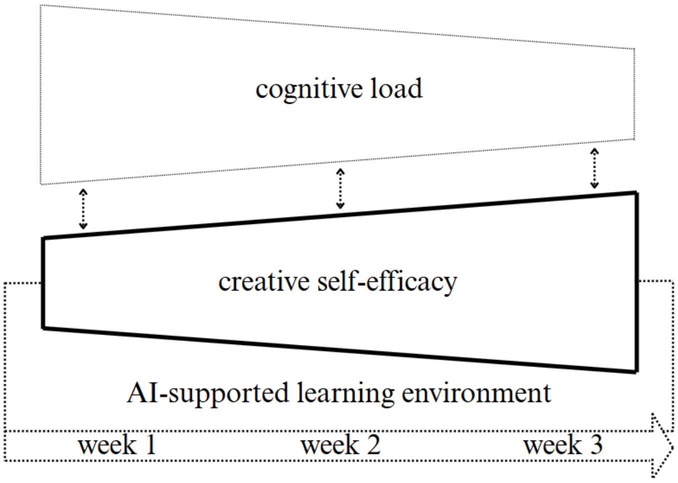

Fig. 1. The hypothesized model.

Methods

Participants

Initially, fifteen Year 9 students from a private Australian Christian secondary school participated in this study, which focused on The Mars Rover Challenge. This challenge was part of a three-week module within a broader extracurricular programme about programming and AI. Convenience sampling was applied in this study, as all students enrolled in the broader extracurricular programme were invited to participate, without further selection criteria. However, one student was frequently ill, and one withdrew from the programme, resulting in a final sample of thirteen participants. The extracurricular programme was attended exclusively by boys, with an average age of 15 years (*SD* = .59), ranging from 14 to 16 years.

Procedure

The Mars Rover Challenge tasked teams (4 to 5 students) with assembling a Mars Rover during eight 50-minute sessions with the assistance of an AI-based vision analytics tool. This study employs a repeated measures design, as data were collected from thirteen students who were intensively studied for three weeks. This repeated type of data collection allowed for the detection of short-term changes in CSE and CL and enabled detailed exploration of the relationship between these two concepts. Throughout the study, students completed brief paper-and-pencil surveys, all taking approximately five minutes to complete (see Figure 1 for a schedule of survey distribution across sessions). The surveys were administered in class by a teacher and a researcher. The week before the first session in September 2024, the first measurement took place to collect data on levels of CSE (see Figure 1, T0). In the first and second week there was one 50-minute session of The Mars Rover Challenge on Monday and there were two consecutive 50-minute sessions on Thursday. In the third week, there was one session on Monday and one on Thursday. On three different moments (before, during, and after each session) surveys were handed out in class. Prior to each session data were collected on

Figure 1

Schedule of survey distribution across sessions.

week	session	day	before	during	after
0	0	Monday	T0	-	-
1	1	Monday	T1a	T2b	T3c
1	2	Thursday	T4a	T5b	T6c
1	3	Thursday	-	T7b	T8c
2	4	Monday	T9a	T10b	T11c
2	5	Thursday	T12a	T13b	-
2	6	Thursday	-	T14b	T15c
3	7	Monday	T16a	T17b	T18c
3	8	Thursday	T19a	T20b	T21c

Note. Data on T0 were gathered the week before the programme started.

CSE (T1a, T4a, etc.). During and after each session data were gathered on CSE and CL (T2b, T5b, etc., and T3c, T6c, etc.). The Human Research Ethics Committee of the University of South Australia reviewed and approved this study. The data were made anonymous by replacing students' names with a number. Informed consent was obtained from both students and their parents for participation in the study.

Instruments

Creative self-efficacy (CSE) was measured using an instrument developed by Tierney and Farmer (2002) consisting of three statements: "I have confidence in my ability to solve problems creatively", "I feel that I am good at generating novel ideas", and "I am good at finding creative ways to solve problems". Students rated each statement on a 0 to 100 scale, with 0 indicating "not at all confident" and 100 indicating "extremely confident". This approach aligns with Bandura's recommendations for self-efficacy measurements, by offering greater sensitivity than traditional Likert scales (Bandura, 2005). CSE scores were computed as the mean of the three items at each measurement point, then divided by 10, yielding final scores ranging from 0 to 10. All participants completed all three items, so no adjustments were necessary. By evaluating their instrument in different contexts, Tierney and Farmer (2002) examined and provided evidence for the validity of their instrument for assessing CSE. The measure demonstrated strong reliability (Cronbach's $\alpha = .87$) within this study.

To assess cognitive load (CL), students were asked to reflect on the past 30 minutes and report the level of mental effort they had invested in the task. This was measured using a 9-point rating scale, where 1 represented "very, very low mental effort" and 9 represented "very, very high mental effort." This single-item measure was originally developed by Paas (1992). It has demonstrated strong reliability, with a reported Cronbach's α of .90, based on the covariance between students' self-reported CL during instructional and test tasks. Additionally, subjective measures of mental effort have demonstrated high validity in assessing CL (O'Donnell & Eggemeier, 1986, as cited in Paas, 1992).

Data analysis plan

The analyses were performed using IBM SPSS Statistics for Windows, Version 19.0. Standardized residuals and Cook's distances were generated to identify potential outliers. Because of the small sample size, only extreme outliers with Cook's distances exceeding 1 or standardized residuals exceeding 3 were replaced with a missing value. To initially inspect the data, the mean and standard deviation were calculated for all available data on CSE and CL. In addition, Pearson correlation coefficients were computed for the variables included in one or both hypotheses – CSE, CL, session, and moment – as well as for overall survey timing, which was examined for descriptive purposes but was not part of the formal hypotheses. The variable session refers to during which out of the eight sessions the survey was completed (see Figure 1, sessions). Moment indicates the timing within each session (i.e., before, during, or after) the survey was filled in, while survey timing refers to the overall order of the 21 survey time points (T1a to T21c). For all variables, a baseline measurement prior to the start of the programme (T0) was included. To gain further insight, correlations between CSE and CL were also examined separately for each session. Subsequently, Generalized Estimating Equations (GEE) analyses were executed for both hypotheses. This approach was selected because it is well suited for repeated measures data, as it accounts for the correlated nature of observations within individuals. Moreover, GEE is appropriate for smaller, more unbalanced samples, which was essential in this study given that the number of moments a survey was filled in could vary per session, and some participants were absent for one or multiple sessions. GEE automatically applies listwise deletion, meaning that only the specific time points with missing data for a participant are excluded from the analysis, while other observations from the same participant remain in the analysis (Awalludin et al., 2020).

Prior to conducting these analyses, several assumptions and model specifications were reviewed. In contrast to traditional linear regression analyses, GEE do not require homoscedasticity, but do assume normality of the response variables, linearity between the predictor and dependent variable, and multicollinearity between the fixed variables. Additionally, GEE assume correlated responses, which can be evaluated by comparing consistency between different correlation structures. Moreover, when comparing these structures, the best one for interpreting results can be selected by comparing quasi-likelihood under the independence model criterion (Awalluddin et al., 2020).

For the first hypothesis, the GEE model included CSE as dependent variable and session and moment as independent covariates. Normality of CSE was assessed using a histogram and P-P plot. Linearity between the predictor variables session and moment and the dependent variable CSE was checked using a scatterplot of standardized residuals versus standardized predicted values. To assess potential multicollinearity between the fixed factors session and moment, the correlation coefficient between session and moment was calculated to check whether it did not exceed .80. Moreover, multicollinearity diagnostics were examined to check whether the variance inflation factor (VIF) values were below 10, and the tolerance values exceeded .10. To determine the most robust model, both exchangeable and independent correlation structures were compared using the quasi-likelihood under the independence model criterion (QIC). Generally, the model with the lowest QIC is considered the best fit. However, to assess whether within-subject responses were correlated, consistency in the significance of main and interaction effects across both models was also evaluated. When inconsistencies were found, both models were examined further.

For the second hypothesis, the GEE model was estimated with CL as the dependent variable and CSE and session as covariates. The same assumptions assessed for hypothesis 1 were evaluated using identical procedures. Normality of CL was inspected, linearity was examined between each predictor (CSE and session) and the outcome variable (CL), and multicollinearity between the predictors was assessed. GEE models with both independent and exchangeable correlation structures were evaluated and compared to evaluate response correlation and determine the best fitting model.

Results

Assumption checks and model selection

Outliers were identified using Cook's distances and standardized residuals. One outlier on CSE with a standardized residual exceeding 5 was replaced with a missing value. No outliers on CL were detected. Normality of CSE and CL were inspected, using histograms and P-P plots (see Appendix B1). The distribution of CSE was approximately normal, whereas CL exhibited a moderate, but still acceptable, negative skew. Linearity was assessed using scatterplots of standardized residuals versus standardized predicted values (see Appendix B2). These plots showed no clear patterns for both analyses, indicating that the assumption of linearity was met. The assumption of multicollinearity was assessed by calculating correlation coefficients and assessing VIF and tolerance values (see Appendix B3). No indication of multicollinearity was found for either session and moment (r =.21; VIF = 1.05; tolerance = .95), or CSE and session (r = .32; VIF = 1.10; tolerance = .91), since Pearson's r was less than .80 for both analyses, VIF values were less than 10, and tolerance values did exceed .10.

Quasi-likelihood under the independence model criterion (QIC) was used to compare GEE models with exchangeable and independent working correlation structures. A lower QIC indicates better model fit. For the first hypothesis, the exchangeable structure showed a slightly lower QIC (301.71) than the independent structure (305.18). Since both models yielded consistent significance levels for main and interaction effects (see Appendix B4), only the exchangeable model was further analysed. For the second hypothesis, the exchangeable structure again showed a lower QIC (438.17) compared to the independent structure (443.79). However, the significance of main and interaction effects differed across models (see Appendix B5), so both models were reviewed.

Descriptive statistics and correlation analysis

Table 1 presents the overall mean and standard deviation for each dependent variable, calculated from the combined responses across all survey time points. It also includes correlations between the dependent and independent variables. Correlations between CSE, CL, and session were calculated using listwise deletion, including only data from measurement moments where both CSE and CL were assessed. Cases with missing data on any of the variables involved in each correlation were excluded. Descriptive statistics, on the other hand, were calculated using all available data. Creative self-efficacy (CSE) showed significant positive correlations with session ($r = .32$, $p < .001$), moment ($r = .20$, $p < .01$), and survey timing ($r = .33$, $p < .001$). Cognitive load (CL) was significantly positively correlated only with CSE ($r = .33$, $p < .001$).

Table 1

Descriptive statistics and correlations among the variables for hypothesis 1 and 2.

Variables	***M***	***SD***	**CSE**	**session**	**moment**	**survey**
CSE	7.98	1.12	1	.32***	.20**	.33***
CL	6.27	1.77	.33***	-.04	.00	-.04

Note. Descriptive statistics reflect all available data per variable (CSE: $N = 240$; CL: $N = 160$). Correlations are based on listwise deletion ($N = 157$). CSE = creative self-efficacy; CL = cognitive load; survey = survey timing.

* $p < .05$, ** $p < .01$, *** $p < .001$.

For each session, correlations between CSE and CL were calculated across all measured moments (see Table 2). CL was only assessed during and after each session, so only those time points were included in the analysis. In principle, this would yield a maximum of 26 data points per session. However, due to listwise deletion, cases with missing data on either CSE or CL were excluded from the correlation analysis for a given session, resulting in varying numbers of observations across the eight sessions. This variation was primarily due to participant absences – particularly in sessions 5 and 6 – and to the absence of an “after” measurement in session 5 (see Figure 1). CSE and CL were only significantly positively correlated for session 1 ($r = .71$, $p < .001$), session 3 (r = .53, $p < .01$) and session 4 ($r = .73$, $p < .001$). Session 2 showed a positive, though unsignificant, correlation between CSE and CL ($r = .30$, $p = .20$). In contrast, correlation coefficients for sessions 5 through 8 were negligeable (rs < .12; ps > .60).

Table 2

Correlations of levels of creative self-efficacy (CSE) and cognitive load (CL) for each session.

Variables	CL S1	CL S2	CL S3	CL S4	CL S5	CL S6	CL S7	CL S8
CSE	.71***	.30	.53**	.73***	-.02	-.07	-.05	.11
Observations	24	20	22	22	8	15	24	22

Note. Correlation is based on listwise deletion. S1 = session 1; S2 = session 2; etc.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Main results: Generalized Estimating Equations

First, to test hypothesis 1 – that students' CSE will increase during three weeks in an AI-supported learning environment – the predictive effects of session, moment and the interaction between both variables on CSE were analysed using only exchangeable correlation structures, since independent correlation structures generated similar results (see Table 3). The main effect of session on CSE was significant ($B = .12$, $p = .02$). However, the main effect of moment on CSE was marginal ($B = .10$, $p = .08$), and the interaction effect of moment and session was not significant ($B = -.00$, $p = .95$).

Table 3

Predicting creative self-efficacy using session, moment, and interaction.

Predictor	B	p-value
Session	.12	.02*
Moment	.10	.08
Session x Moment	-.00	.95

Note. Generalized Estimating Equation model with exchangeable correlation structure.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Second, to test hypothesis 2 – that higher levels of CSE are associated with lower CL during three weeks in an AI-supported learning environment – the relationships between CSE, session, and their interaction with CL were analysed using both exchangeable and independent correlation structures, as these models did not yield similar significance levels (see Table 4). The main effect of CSE on CL was robust, with both the exchangeable (B = 1.12, p < .001) and independent (B = 1.08, p < .001) models indicating a significant positive association. However, the main effect of session (B = .90, p =.02) and the interaction effect between session and CSE (B = –.12, p = .01) were only significant in the exchangeable structure. Although these effects remained in the same direction in the independent model (B = 0.82, p = .12 for session; B = –0.11, p = .07 for the interaction), they were not significant, indicating some sensitivity when interpreting the results is appropriate.

Table 4

Predicting cognitive load using CSE, session, and interaction.

Structure	**Exchangeable**		**Independent**	
Predictor	**B**	**p-value**	**B**	**p-value**
CSE	1.12	<.01**	1.08	<.01**
Session	.90	.02*	0.82	.12
CSE x Session	-.12	.01*	-.11	.07

Note. Generalized Estimating Equation model with exchangeable and independent correlation structure. CSE = creative self-efficacy

* p < .05, ** p <.01, *** p <.001.

Taken together, the results indicate that creative self-efficacy (CSE) increased significantly across sessions and showed a marginal increase from the beginning to end of each session, supporting hypothesis 1. Contrary to hypothesis 2, higher levels of CSE were associated with higher levels of cognitive load (CL). However, a significant interaction effect in the exchangeable model suggests that this relationship weakened over time, indicating that the positive association between CSE and CL was strongest in earlier sessions. These findings are further explored in the discussion section.

Discussion

Research has shown that when learners are supported within their zone of proximal development (ZPD), this can help strengthen their creative self-efficacy (CSE) and regulate cognitive load (CL). AI-supported learning environments are promising tools for providing scaffolded support, but there is still limited research into how CSE and CL develop in these environments. Addressing this gap, this study explored the development of CSE and the relationship between CSE and CL in a learning environment where students built a Mars Rover with scaffolded support from an AI-based vision analytics tool. It focused on adolescent secondary school students, since during this developmental phase CSE often decreases (i.e., 'adolescent slump').

The positive development of CSE

The findings of this study indicate that CSE increased over the course of eight sessions within a three-week AI-supported learning environment, because session had a significant positive effect on CSE. Although moment (whether a survey was filled in before, during, or after a session) appeared to have a marginal positive effect on CSE levels, this effect did not reach statistical significance. Furthermore, no interaction was found between session and moment, indicating that the relationship between moment and CSE remained consistent across sessions. These results suggest that AI-supported learning environments like the one used in this study can support the development of CSE in adolescents, as long as they offer scaffolded learning experiences. This supports the idea that when students engage in tasks that are just beyond what they can do alone, but achievable with guidance, they experience progress, which helps them build confidence in their abilities (Bandura, 1982; Walker, 2010; Wood, 1976). In other words, when AI tools provide learning tasks within students' ZPD, learners' CSE can grow. These findings are in line with studies in other populations, which revealed AI's possibilities to foster CSE in students amongst business administration students (Yin et al., 2024), and pre-service teachers (Saritepeci & Durak, 2024). To our best knowledge, this is one of the first studies to explore how CSE develops in AI-supported learning environments, and the first to focus on adolescents. It offers valuable insights into how AI can support the development of CSE in adolescent learners.

The positive relationship between creative self-efficacy and cognitive load

The findings of this study indicate a significant positive relationship between CSE and CL, contradicting former research pointing out that students with higher CSE typically view a task as more manageable, therefore experiencing lower CL (Redifer et al., 2021). A possible explanation for this difference in results is that Redifer et al.'s study (2021) focused on undergraduate students and did not account for the influence of AI-support. Another surprising finding was that CL seemed to increase over the course of eight sessions. This outcome is unexpected, given that the AI-supported learning environment was designed to offer scaffolding – typically associated with reducing CL (Sweller, 1988). AI can scaffold learning by helping students focus on manageable parts of a task, breaking down complex activities, providing step-by-step guidance, and verifying learners' actions (Wood et al., 1976; Triana-Vera & López-Vargas, 2025). However, these findings should be interpreted with caution, since there appears to be little prior research on the development of CL in AI-supported settings. Furthermore, although both independent and exchangeable models showed a positive relationship between CL and session, this effect only reached significance in the exchangeable model.

The weakening link between creative self-efficacy and cognitive load

Remarkably, the results suggest that the relationship between CSE and CL weakened over time, with the exchangeable structure showing significant and the independent structure showing marginal interaction between CSE and session. This is also reflected in the correlation analysis: CSE and CL were significantly correlated in the earlier sessions (sessions 1, 3, and 4), but this connection was no longer evident in later sessions. Together, these findings suggest that although CSE and CL were positively related, this relationship weakened over time, indicating a reduced influence of CSE on CL as students became more familiar with the learning environment. As far as we know, no previous research has examined how CSE and CL develop together over time, which makes it difficult to fully explain this pattern. A plausible explanation is that students who felt confident from the beginning were more willing to invest cognitive effort and reported higher CL accordingly. Over time, as the tasks became more familiar, the connection between confidence and mental effort may have declined. This interpretation aligns with cognitive load theory (Sweller, 1988), which suggests that CL tends to decrease as tasks become less complex or novel. Although CL did not decrease in this study, its increase over time was less strong than the increase in CSE, which may explain why their relationship weakened over time. While this interpretation remains speculative due to the limited research on the relationship between CSE and CL, it offers valuable insights into how these constructs may interact over time within AI-supported learning environments.

Limitations and contributions

Although this study contributes to the still limited body of research on the development of CSE and CL in AI-supported learning environments, it also has several limitations. First, the sample used in this study was not very diverse. All participants had voluntarily enrolled in a programme about programming and AI, likely making them more interested in AI than the average student. In addition, the group consisted exclusively of boys attending a private Christian school in Australia. This homogeneity limits the generalizability of the findings to broader student populations. Future research would benefit from including a more diverse range of students in terms gender, school type, cultural background, and educational system to offer more comprehensive insights and potentially different results.

The second limitation also concerns sampling, since the overall sample size was relatively small and fluctuated across sessions due to student absences. While this does not compromise the primary analysis, given that the Generalized Estimating Equations method is well suited for repeated measures data with unbalanced samples, it may have influenced the strength and stability of the session-specific correlations between CSE and CL. This is particularly relevant for sessions 5 and 6, where the number of observations was low, potentially making it harder to detect significant relationships even if they existed.

Third, this study relied exclusively on self-reported measures for both CL and CSE. While the instruments used were validated, self-reports alone may not fully capture the complexity of students' experiences. For instance, students might have responded in socially desirable ways, which could have influenced the results. Additionally, the surveys did not provide insights into which types of scaffolding were perceived as most supportive in fostering CSE. Incorporating qualitative data—such as interviews or open-ended survey questions—could offer a deeper understanding of how students experience AI-supported scaffolding and how it relates to CL and the development of CSE.

Fourth, the study's three-week duration may have limited the ability to observe long-term developments in CSE and CL. Although the findings offer valuable insights into short-term changes, longer interventions might reveal different patterns. As the adolescent slump in CSE typically unfolds over a longer time span, it remains unclear whether AI-supported learning environments can effectively mitigate this decline. Future research could investigate whether the positive trends identified in this study persist when integrated into longer-term educational programs. Despite these limitations, this study provides an initial contribution to a currently underexplored area of research on the development of CSE and CL in an AI-supported learning environment among adolescents. It offers a foundation for future studies to further examine how these concepts develop and interact in digital learning environments.

Implications

This study has several implications for both research and practice. It adds to the growing evidence that scaffolded AI support can help foster CSE. Previous studies found this effect in higher education (e.g., Saritepeci & Durak, 2024; Yin et al., 2024), and this study extends those findings to adolescents in secondary education. However, since this appears to be the first study to examine how CSE develops in adolescents within AI-supported environments, more research is needed to replicate and expand on these results. Future studies could explore AI-supported environments that provide scaffolded support for a broader range of creative tasks – beyond the technological and construction-based focus of the current study – to include domains such as other STEM activities or creative writing. Additionally, research involving a larger and more diverse sample, as well as a longer study period, would offer deeper insights. For instance, investigating the use of AI-based scaffolding within a compulsory subject spanning two academic years could allow for longitudinal measurement of CSE at regular intervals. This would make it possible to examine how these constructs develop over time and assess the potential of AI-supported environments in minimizing the adolescent slump in CSE.

Furthermore, future research could investigate the decreasing relationship between CSE and CL in greater depth, both within and beyond AI-supported learning environments. Exploring this pattern in a larger and more diverse sample over an extended period would allow for a more nuanced understanding of how these constructs interact over time. One promising direction would be to examine potential mediating variables – particularly students' willingness to invest cognitive effort. A plausible explanation for the observed weakening of the CSE–CL relationship mentioned before is that students with higher levels of CSE may have initially been more motivated to engage deeply with the learning tasks, thereby reporting higher CL. As the tasks became more familiar, this additional investment may have diminished, reducing the strength of the association. Including measures of student willingness to invest cognitive effort could offer valuable insights in the evolving relationship between CSE and CL. Moreover, it could be interesting to distinguish between types of CL when further exploring the relationship between CSE and CL, because while high levels of extraneous and intrinsic load can hinder learning, germane load directly supports it (van Merriënboer et al., 2006).

Finally, this study offers practical implications for education by demonstrating how AI-supported scaffolding can help address the decline in CSE observed during adolescence. By managing CL and supporting student autonomy, AI tools like the vision analytics tool explored in this study can foster CSE through manageable tasks and timely, student-triggered feedback. Integrating such tools into broader curricula over longer periods may strengthen their impact. Beyond the Mars Rover context, AI-supported scaffolding holds promise in other creative domains – such as digital storytelling (Saritepeci & Durak, 2024) or complex problem-solving (Carotenuto et al., 2021) – where breaking tasks into subgoals and offering flexible guidance can help students experience success and a sense of responsibility, likely increasing their CSE (Walker, 2010; Wood et al., 1976). As CSE is positively related to creativity (Herianto et al., 2024; Tierney & Farmer, 2011; Wang et al., 2024), this may contribute to counteracting the broader decline in creativity during adolescence (Gralewski et al., 2016).

Conclusions

In summary, this study offers initial insights into how creative self-efficacy (CSE) and cognitive load (CL) develop and interact in adolescents working within an AI-supported learning environment. While the sample was small and not diverse, the findings provide promising evidence that scaffolded AI support can help foster CSE and influence how learners experience CL. CSE increased significantly over time, suggesting that when students are guided through learning tasks within their zone of proximal development, their sense of creative competence can grow. At the same time, the weakening relationship between CSE and CL across sessions may reflect a shift towards more efficient learning, as students put in less cognitive effort once tasks became more familiar. Taken together, these findings highlight the potential of AI-supported tools to strengthen creative self-beliefs in adolescence – a developmental stage where these beliefs are often at risk of dropping.

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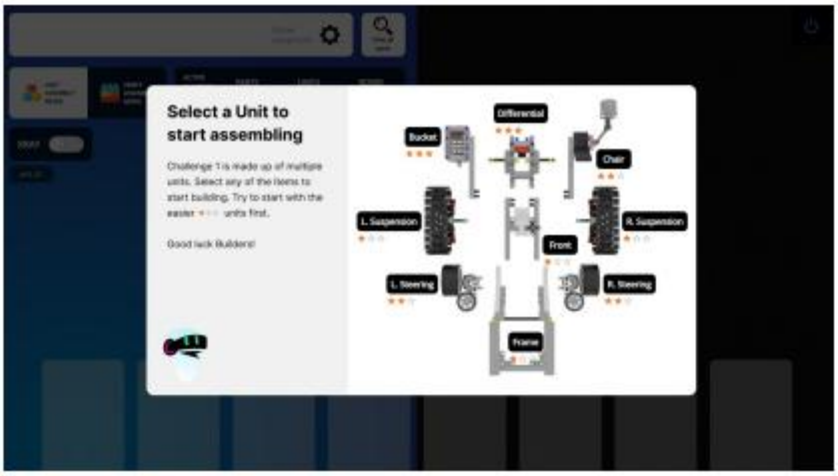
Appendix A1

Breaking down tasks in manageable components

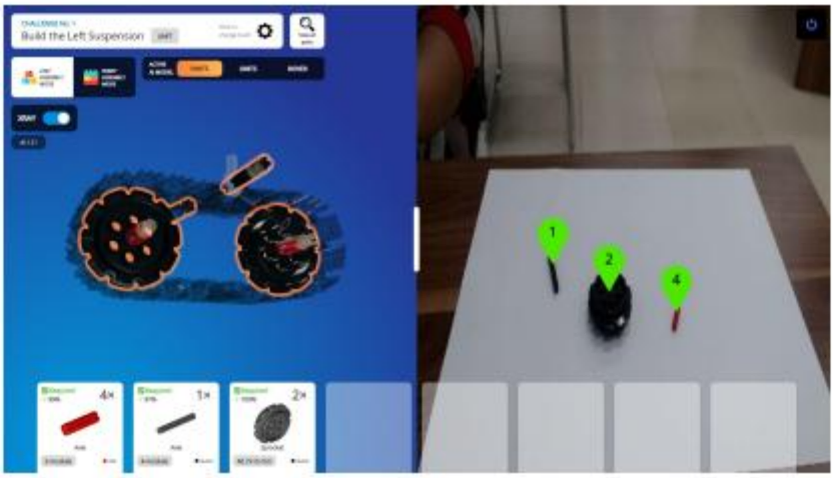
On the final page of the Welcome Screen, Challenge 1 is broken down into various sections. Click on any of the buttons that correspond to the Unit you want to assemble first.



Appendix A2

Guiding learners step by step through construction

Upon placing the lego piece in front of the camera, the 3D object on the left panel will highlight the parts where the lego piece should be placed. You may rotate, zoom in and out the 3D object to serve as your guide in building the unit. You may also toggle the **"XRAY"** button for a clearer view of the 3D object.



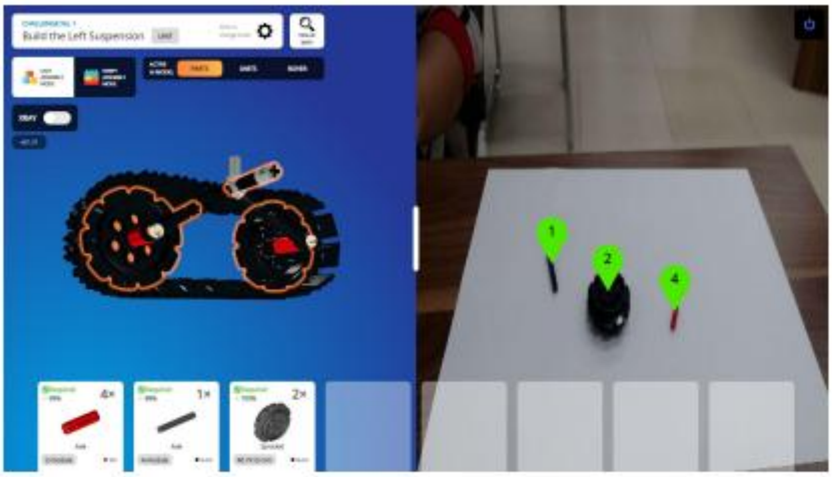
Getting familiar with the Pins & Balloons

Pin/Balloon Icon	Description
	**Highlighted Piece** A balloon on Service Applet window highlighting the verified and required specific part; The number indicates the pieces needed for the unit assembly.
	**Exclude this Piece** A balloon on Service Applet window pointing at the piece which needs to be excluded
	**Not for this Unit** A balloon on Service Applet window pointing at the verified piece but not required for the current unit

Appendix A3

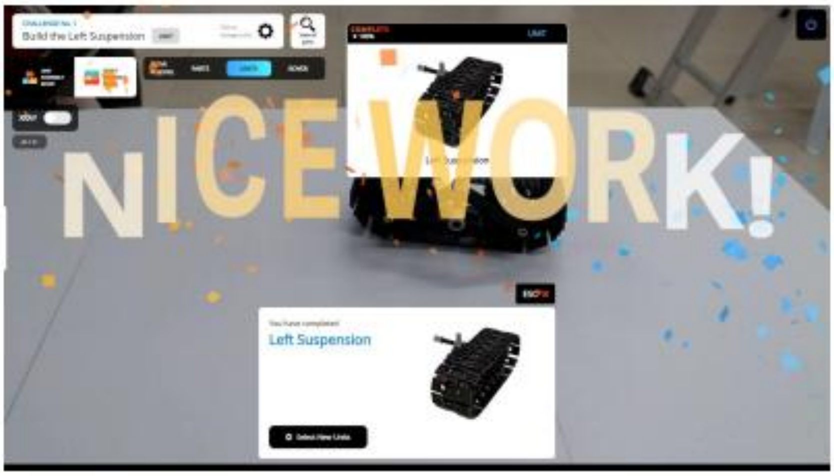
Providing students with feedback

Gather all the required lego pieces for the unit and verify it by placing the piece/s in front of the camera.



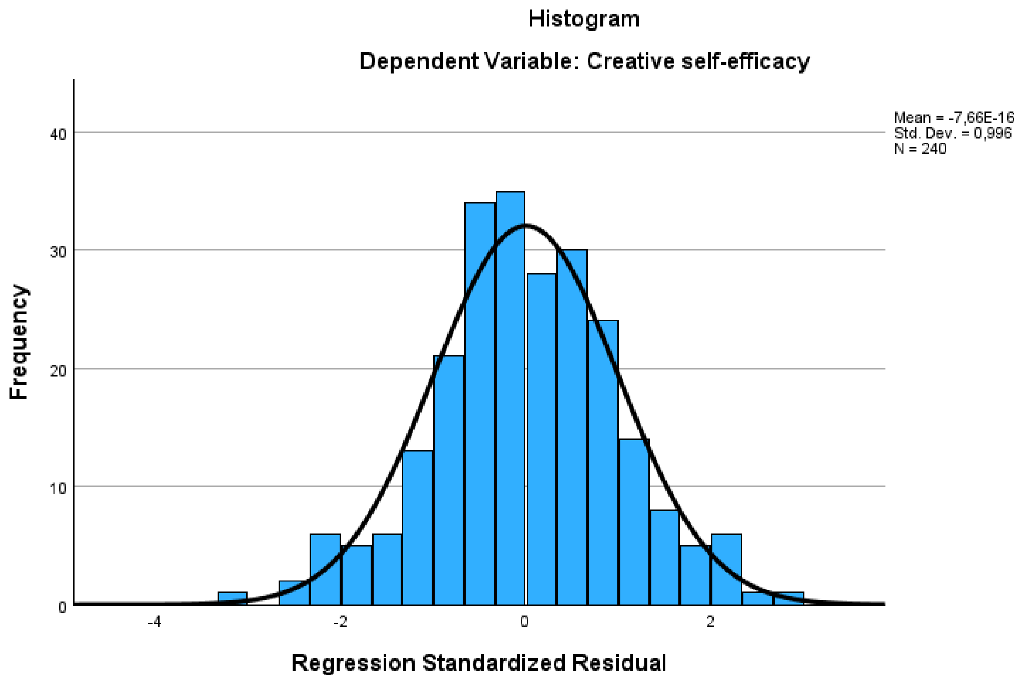
- *A balloon on the Service Applet window pointing at the verified and required specific part indicates that the piece is needed or required for the unit being assembled.*
- *Service Applet is the Window on the right panel of the screen which displays what the sensor is capturing.*
- *The number indicated in the balloon specifies the number of pieces needed for the unit, gather similar lego pieces as indicated to complete all required pieces.*

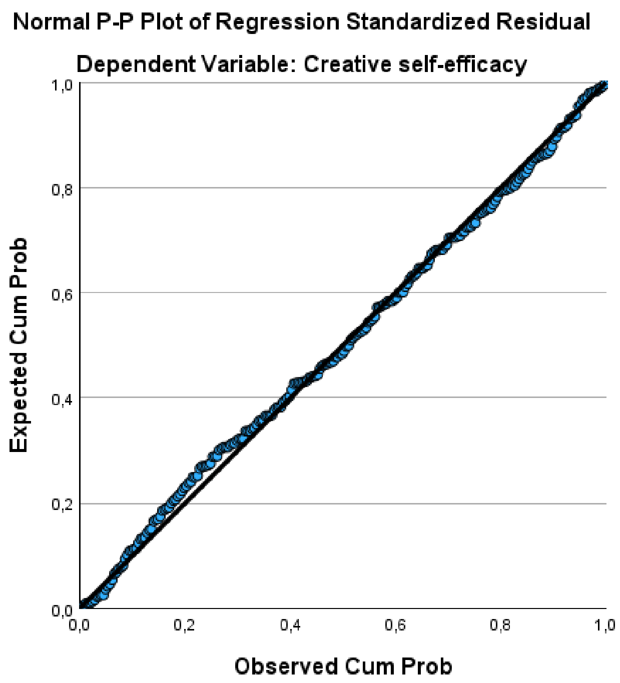
A **"Nice Work"** message will appear once the Builder App detects a complete unit. Press the **"Select New Units"** button to start building the next unit.

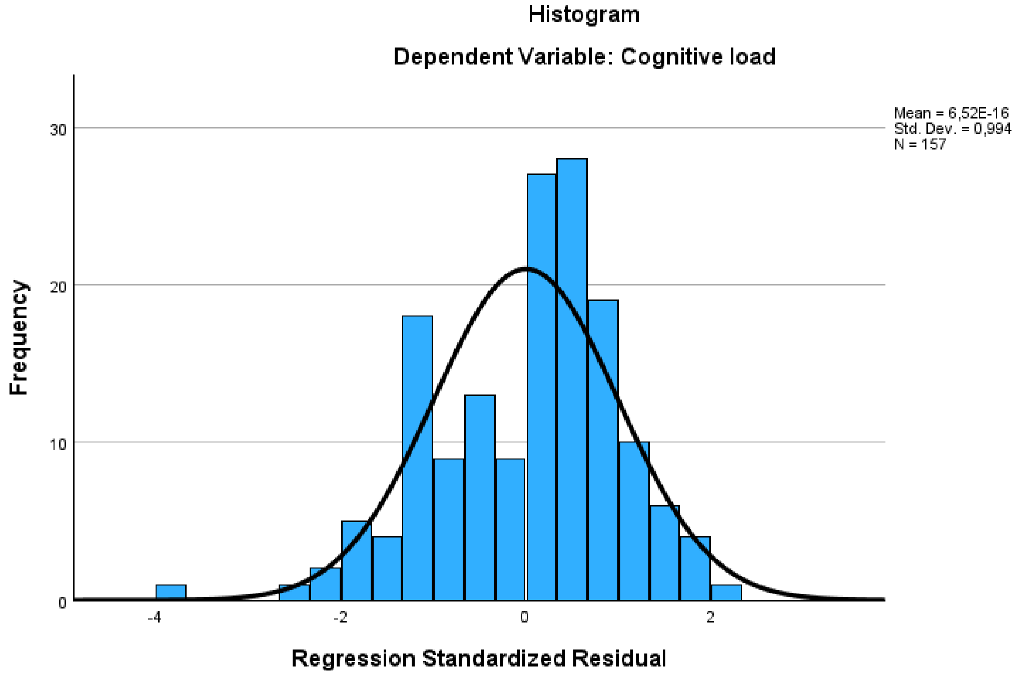


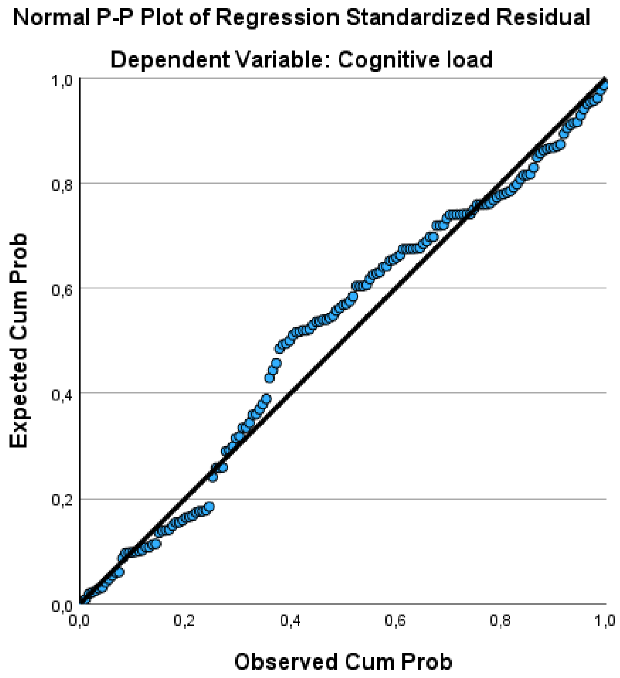
Appendix B1

Normality check



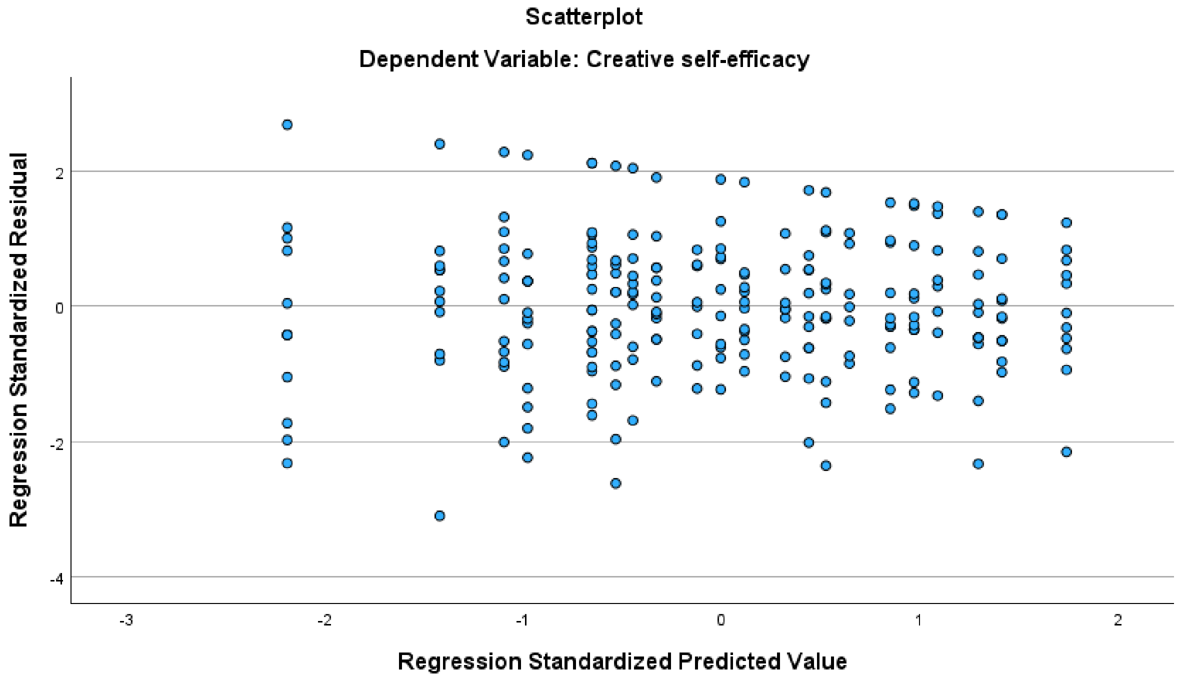


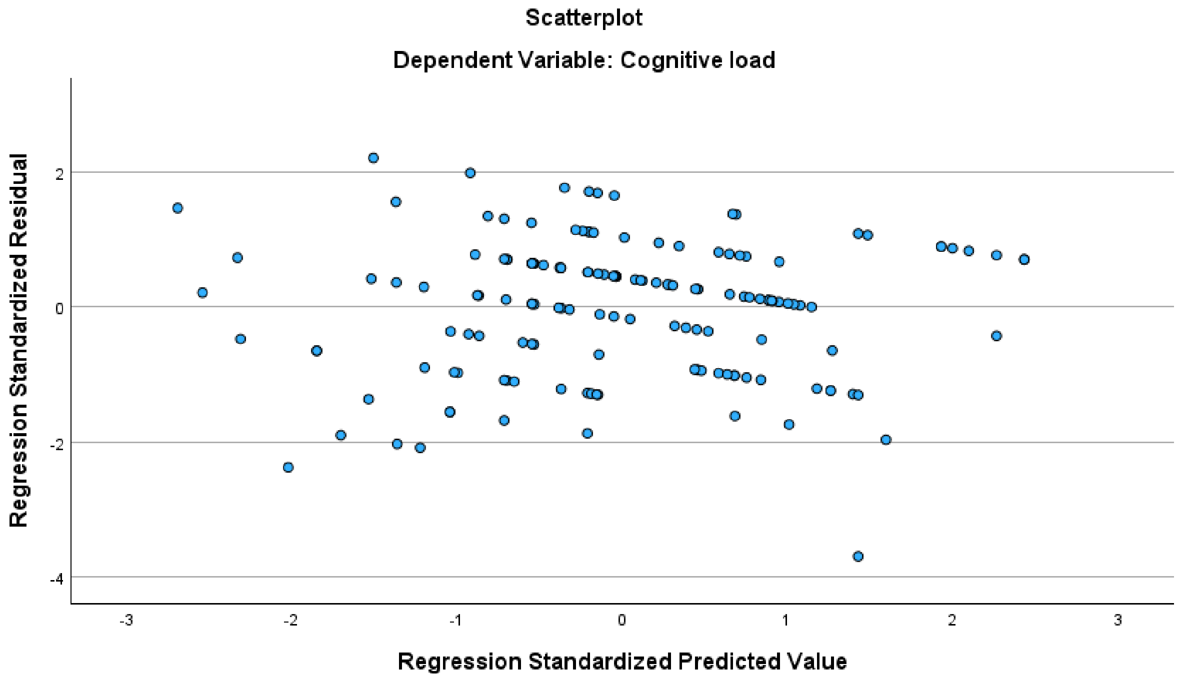

Histogram
Dependent Variable: Cognitive load
Mean = 6,52E-16
Std. Dev. = 0,994
N = 157
Frequency
Regression Standardized Residual
30
20
10
0
-4
-2
0
2


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: Cognitive load
Expected Cum Prob
Observed Cum Prob
1,0
0,8
0,6
0,4
0,2
0,0

Appendix B2

Linearity check





Appendix B3

Multicollinearity check

Correlations

		Session (1-8)	Moment (1-4)
Session (1-8)	Pearson Correlation	1	,213**
	Sig. (2-tailed)		<,001
	N	285	285
Moment (1-4)	Pearson Correlation	,213**	1
	Sig. (2-tailed)	<,001	
	N	285	285

**. Correlation is significant at the 0.01 level (2-tailed).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	6,943	,251		27,702	<,001		
	Session (1-8)	,128	,027	,292	4,680	<,001	,950	1,053
	Moment (1-4)	,175	,083	,133	2,126	,035	,950	1,053

a. Dependent Variable: Creative self-efficacy

Correlations

		Session (1-8)	Creative self-efficacy
Session (1-8)	Pearson Correlation	1	,322**
	Sig. (2-tailed)		<,001
	N	285	240
Creative self-efficacy	Pearson Correlation	,322**	1
	Sig. (2-tailed)	<,001	
	N	240	240

**. Correlation is significant at the 0.01 level (2-tailed).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,615	1,041		1,551	,123		
	Session (1-8)	-,107	,058	-,146	-1,859	,065	,912	1,096
	Creative self-efficacy	,631	,133	,374	4,748	<,001	,912	1,096

a. Dependent Variable: Cognitive load

Appendix B4

GEE models hypothesis 1

Model Information

Dependent Variable		Creative self-efficacy
Probability Distribution		Normal
Link Function		Identity
Subject Effect	1	Number student (given by researcher)
Within-Subject Effect	1	Timing of survey (1-21)
Working Correlation Matrix Structure		Exchangeable

Goodness of Fit[a]

	Value
Quasi Likelihood under Independence Model Criterion (QIC)[b]	301,713
Corrected Quasi Likelihood under Independence Model Criterion (QICC)[b]	280,377

Dependent Variable: Creative self-efficacy
Model: (Intercept), Session (1-8), Moment (1-4), Session (1-8) * Moment (1-4)[a]

a. Information criteria are in smaller-is-better form.

b. Computed using the full log quasi-likelihood function.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	233,080	1	<,001
Session (1-8)	5,080	1	,024
Moment (1-4)	3,125	1	,077
Session (1-8) * Moment (1-4)	,004	1	,947

Dependent Variable: Creative self-efficacy
Model: (Intercept), Session (1-8), Moment (1-4), Session (1-8) * Moment (1-4)

Model Information

Dependent Variable		Creative self-efficacy
Probability Distribution		Normal
Link Function		Identity
Subject Effect	1	Number student (given by researcher)
Within-Subject Effect	1	Timing of survey (1-21)
Working Correlation Matrix Structure		Independent

Goodness of Fit[a]

	Value
Quasi Likelihood under Independence Model Criterion (QIC)[b]	305,179
Corrected Quasi Likelihood under Independence Model Criterion (QICC)[b]	280,255

Dependent Variable: Creative self-efficacy
Model: (Intercept), Session (1-8), Moment (1-4), Session (1-8) * Moment (1-4)

a. Information criteria are in smaller-is-better form.

b. Computed using the full log quasi-likelihood function.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	221,875	1	<,001
Session (1-8)	5,590	1	,018
Moment (1-4)	2,500	1	,114
Session (1-8) * Moment (1-4)	,001	1	,979

Dependent Variable: Creative self-efficacy
Model: (Intercept), Session (1-8), Moment (1-4), Session (1-8) * Moment (1-4)

Appendix B5

GEE models hypothesis 2

Model Information

Dependent Variable		Cognitive load
Probability Distribution		Normal
Link Function		Identity
Subject Effect	1	Number student (given by researcher)
Within-Subject Effect	1	Timing of survey (1-21)
Working Correlation Matrix Structure		Exchangeable

Goodness of Fit[a]

	Value
Quasi Likelihood under Independence Model Criterion (QIC)[b]	438,170
Corrected Quasi Likelihood under Independence Model Criterion (QICC)[b]	425,071

Dependent Variable: Cognitive load
Model: (Intercept), Session (1-8), Creative self-efficacy, Session (1-8) * Creative self-efficacy[a]

a. Information criteria are in smaller-is-better form.

b. Computed using the full log quasi-likelihood function.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	1,249	1	,264
Session (1-8)	5,446	1	,020
Creative self-efficacy	16,117	1	<,001
Session (1-8) * Creative self-efficacy	6,151	1	,013

Dependent Variable: Cognitive load
Model: (Intercept), Session (1-8), Creative self-efficacy, Session (1-8) * Creative self-efficacy

Model Information

Dependent Variable		Cognitive load
Probability Distribution		Normal
Link Function		Identity
Subject Effect	1	Number student (given by researcher)
Within-Subject Effect	1	Timing of survey (1-21)
Working Correlation Matrix Structure		Independent

Goodness of Fit[a]

	Value
Quasi Likelihood under Independence Model Criterion (QIC)[b]	443,787
Corrected Quasi Likelihood under Independence Model Criterion (QICC)[b]	424,603

Dependent Variable: Cognitive load
Model: (Intercept), Session (1-8), Creative self-efficacy, Session (1-8) * Creative self-efficacy[a]

a. Information criteria are in smaller-is-better form.

b. Computed using the full log quasi-likelihood function.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	1,130	1	,288
Session (1-8)	2,443	1	,118
Creative self-efficacy	20,044	1	<,001
Session (1-8) * Creative self-efficacy	3,337	1	,068

Dependent Variable: Cognitive load
Model: (Intercept), Session (1-8), Creative self-efficacy, Session (1-8) * Creative self-efficacy

Appendix C

Declaration of plagiarism

Met ondertekening van deze overeenkomst verklaar ik Pien Roelofs student Pedagogische Wetenschappen van de Erasmus Universiteit Rotterdam, dat ik bij het schrijven van mijn scriptie over het onderwerp CREATIVE SELF-EFFICACY AND COGNITIVE LOAD IN AI-LEARNING geen plagiaat heb gepleegd en dat de scriptie het resultaat is van mijn eigen werk en verwoord is in mijn eigen woorden, behoudens citaten. Daar waar mijn scriptie gebaseerd is op informatie dan wel ideeën van een ander zal ik die ander recht doen door naar diens geraadpleegde werk te verwijzen. Tevens verklaar ik dat ik te allen tijde verantwoordelijk blijf voor het bovenstaande.*

Datum, plaats: Rotterdam, 4-7-2025

Handtekening: