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AI Support in R Coding: Effects on Psychology Students' Self-Efficacy

Abstract

Students struggle with coding in R, often resulting in low R-associated self-efficacy. Given the rise of AI, we examined in five seminars whether AI boosted self-efficacy of 57 students compared to a prior session. However, we found no significant increase in R-associated self-efficacy. Of 11 exploratory analyses we found in one analysis an unexpected result that we interpreted as disappointed expectations. This result underlines the importance to effectively handle students' expectations and experiences when using AI.

Keywords

AI support in R coding, self-efficacy, higher education, psychology

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KI-gestütztes Coden mit R: Wie verändert es das Selbstwirksamkeitserleben Psychologiestudierender?

Zusammenfassung

Psychologiestudierende finden coden in R oft schwierig. Dies kann zu einem niedrigen R-bezogenen Selbstwirksamkeitserleben führen. Wir prüften in fünf Seminaren, ob der KI-Einsatz das Selbstwirksamkeitserleben 57 Studierender in Bezug auf R im Vergleich zu einer Seminarsitzung ohne KI-Einsatz verbesserte. Wir fanden keinen signifikanten Anstieg, jedoch zeigte sich in einer von 11 explorativen Analysen ein unerwartetes Ergebnis. Dieses führten wir auf enttäuschte Erwartungen des KI-Einsatzes zurück. Damit zeigten wir die Wichtigkeit, studentische Erwartungen und ihre vorherigen Erfahrungen beim KI-Einsatz zu bedenken.

Schlagwörter

KI-gestütztes Coden in R, Selbstwirksamkeit, Hochschullehre, Psychologie

1 AI Support in R Coding: Effects on Psychology Students' Self-Efficacy

Artificial intelligence (AI) has become part of higher education, changing how students learn and conduct research. Given that 68% of students reported using AI as a learning aid in 2023 (Garrel et al., 2023), it is crucial that lecturers explore ways to implement AI in their teaching in a useful manner. We designed a study to explore AI's impact in higher education through its practical use in a research seminar. We examined how implementing AI support affected psychology students' self-efficacy in using the statistical program R for data analysis.

Given that students do not select psychology as a subject for the purpose of learning to code, a substantial part of them are surprised by the extent of statistics and R coding required in their studies. Sometimes students even opt for psychology as a subject with the aim of steering clear of mathematical and methodological topics (Macher et al., 2013). Hence, research seminars pose a huge challenge to these students. They have to learn coding while applying their theoretical understanding of statistics in practical settings. These challenges are further compounded by additional difficulties that effect students' self-efficacy.

One of the difficulties they face in coding is the need to adopt computational thinking (Wing, 2006). This type of thinking involves understanding abstract and mathematical concepts, as well as debugging (Yilmaz & Yilmaz, 2023) to identify and fix errors in code. Despite their typically impressive academic records (Bühner, 2023), psychology students often grapple with these difficulties that can erode their self-efficacy in such seminars. Therefore, our study aimed to integrate supportive AI alongside traditional instruction from lecturers and tutors, and assess its impact on students' R-related self-efficacy over several sessions.

1.1 R-associated Self-Efficacy

Mastery of data analysis depends considerably on self-efficacy (Ramalingam & Wiedenbeck, 1998). Self-efficacy can be seen as a task-specific construct (Schunk & Pajares, 2002), e.g. a task can be to employ a *t*-test. However, it can also be seen as domain-specific, such as academic self-efficacy (Elias & MacDonald, 2007). For our study, we required a construct that bridged these two extremes, encompassing more than individual tasks but less than the broader academic context with its diverse challenges. A focus on coding-associated self-efficacy, that refers to a student's effort to solve coding problems even when they are challenging (Ramalingam & Wiedenbeck, 1998), seemed appropriate.

We narrowed this focus even further to R-associated self-efficacy (RaSE). In this study, our aim was to boost students' RaSE. This aim is crucial because improved RaSE can lead students to perform better in data analysis, increase their persistence when facing coding problems, and foster greater openness to engage with complex R-based projects that are necessary throughout their studies. Moreover, as R is widely used in various fields for data science, boosting students' RaSE can enhance their academic and professional prospects.

1.2 AI Support in R Instruction

We decided to implement AI in research seminars with the aim of boosting students' RaSE. This decision was based on AI's potential to provide personalized and immediate support, which we hypothesized can positively affect students' overall RaSE.

In the context of coding in general and R instruction in particular, AI refers to advanced generative language models that can understand and generate code. Such AI tools can analyze code snippets, answer coding-related questions, suggest improvements, and even generate code based on natural language descriptions. Therefore, AI tools can act as tutoring systems, providing real-time support and personalized guidance to students.

While AI offers several benefits in a coding context, it is important to note that there are also challenges. By leveraging AI's strengths while being mindful of its limits, we aimed to create a learning environment that can boost students' self-efficacy in tackling diverse R-associated tasks.

1.2.1 Benefits

One substantial benefit of AI in R instruction is its ability to act as a personal tutor. AI can provide immediate feedback (Narciss, 2020), which we see as crucial for boosting students' self-efficacy. When students struggle with specific R tasks, AI can provide instant support for R tasks, offering explanations, syntax corrections, or alternative approaches, unlike traditional teaching methods where students have to wait for answers. Instant AI support not only helps students overcome immediate obstacles but also reinforces a belief in their ability to solve R tasks, thereby boosting their RaSE.

AI also offers a personalized, judgment-free learning environment that adapts to diverse working paces, from students needing extra time on challenging concepts to gifted students seeking advanced content. Students interact freely with AI, repeating questions or exploring alternatives without embarrassment, while AI adjusts complexity to their understanding. This flexibility enables optimal progression for all – whether delving deeper into difficult topics or rapidly advancing through familiar material – surpassing traditional classroom limitations. This personalized learning approach aligns with the self-determination theory, suggesting that autonomy is crucial for intrinsic motivation and psychological well-being (Ryan & Deci, 2000). By allowing students to progress at their own pace without fear of judgement from peers, AI can positively affect students' RaSE.

Moreover, AI extends its benefits by providing support tailored to diverse personal circumstances and needs. This is especially valuable for students facing specific challenges such as disabilities, or language difficulties. Such conditions often hinder students' ability to discuss potential solutions with peers (Yilmaz & Yilmaz, 2023) or seek support from lecturers or tutors (Nelson-Le Gall, 1985). For example, students with language barriers can benefit from AI's ability to rephrase explanations of complex statistical or coding concepts in simpler terms or even in their mother tongue.

Collectively, these benefits support our goal of enhancing learning experiences, ensuring all students receive the necessary support for academic success and thus boosting their RaSE.

1.2.2 Challenges

However, implementing AI also entails some challenges. One challenge of AI-generated responses is that they are not always wholly accurate. Therefore, it is essential for students to carefully assess the accuracy of these responses. Yet, in coding, students can instantly verify the effectiveness of solutions. Nonetheless, verifying whether a solution achieves an intended outcome can be difficult, especially with a large number of data points. Moreover, this verification process is an extra step that some students fail to undertake, relying too heavily on AI (Darvishi et al., 2024). Since the verification process requires considerable prior experience in R, we implemented AI in the final stage of the seminar.

Another challenge is that AI often generates responses that exceed students' abilities, as it does not always align with previously covered content. This is particularly evident with browser-based AI, which sometimes provides lengthy code for simple questions. Inexperienced students struggle to identify the relevant parts of the response and understand the offered R code. This mismatch can undermine students' RaSE, making them feel their skills are inadequate when confronted with advanced code. This was another reason for implementing AI late in the seminar.

1.2.3 Implementation

Still, some students already used AI unsupervised. It seemed wise to address these challenges, providing guidance on how to effectively use AI for coding. Such guidance can positively affect students' RaSE in several ways. Firstly, it empowers students to navigate complex AI-generated responses, thereby enhancing their success rate. Secondly, it allows students to overcome obstacles autonomously, without relying on human support with limited resources. This sense of autonomy, even with AI support, can significantly boost their RaSE. Students learn that they can tackle challenging code by effectively leveraging AI tools, which is a valuable skill in itself.

For all these reasons, we implemented AI (ChatGPT 3.5 from open.ai) in the last two sessions of our research seminar. With this timing, we ensured students had developed a solid foundation in R and data analysis before introducing AI, allowing them to critically evaluate AI-generated code and use it as a supportive tool rather than a crutch (Darvishi et al., 2024). Prior to implementing AI, we provided guidelines on ethical use and discussed AI's limitations, preparing students to use AI appropriately and confidently. With this approach we aimed to boost students' RaSE by empowering them to leverage AI effectively while maintaining their autonomy in problem-solving. Their realization that they will be doing things correctly can further reinforce their RaSE.

1.3 Hypothesis

Due to implementing AI late in our research seminar, we expected that RaSE at the end of the last task (Experiment 4) was higher than at the end of the previous task (Experiment 3). We assumed the boost in RaSE was mainly driven by the AI support.

2 Methods

2.1 Sample

Between October 2023 and January 2024, three lecturers taught 91 students in five seminar groups. We asked these students to participate in our study. At the relevant assessment times, 57 students (15 men, 42 women) provided data. To ensure anonymity, we categorized age: 47 students were younger than 23 years and 10 students were older than 22 years.

2.2 Procedure and Material

In the seminar, students learned how to analyze data of four psychological experiments using R. Each lecturer was supported by a student tutor for R associated tasks. All students wrote three reports about the methods and results based on their analyses.

In Experiment 1, the lecturers demonstrated the necessary R code in two sessions of 135 min each. In the Experiments 2–4, the students autonomously analyzed data under the guidance of their lecturers, with each experiment lasting three sessions (Fig. 1). The sequence of the three sessions for each experiment remained consistent: 1) General data quality control and demographic analyses, 2) Data cleaning and preparation for analyses, 3) Descriptive and inferential analyses including effect sizes, post-hoc analyses, and plots. Students were allowed to work in teams in all sessions.

1 no R	2 R Revision & ggplot2	3+4 R Demonstration Experiment 1 Anchor	5+6+7 R Experiment 2 Stroop	8+9+10 R Experiment 3 Change Blindness	11+12+13 R Experiment 4 False Friends

Fig. 1: Semester schedule. Line 1: Sessions.

In Experiments 1 and 2, the inferential analyses were a *t*-test for dependent samples. In Experiment 3 it was a two-way repeated measures Analysis of Variance. Experiment 4 was analyzed with a one-way repeated measures Analysis of Variance and planned contrasts.

In Session 12 (Experiment 4), an introduction to the potential use of ChatGPT 3.5 was demonstrated when coding in R. Next, the students corrected a R script with purposely introduced errors. This R script closely resembled the scripts of the previous experiments. Possible errors were typos, syntax errors, and incorrect use of functions (Fig. 2). For the last type of error, we also provided correct solutions in the script (Fig. 2, 382f.).

```
379 # anonymized names for subjects [Anonyme Probanden-Bezeichnung]
380 x$participant <- rep(x = 1:nSubjects, each = nRows)
381 head(x$participant, nRows + 3)
382 # expected solution [Lösung für die KI-Sitzung] 2024_01:
383 # [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2
```

Fig. 2: Short example of an error. In Line 380, the previously incorrect argument “times” had to be changed to “each”.

Students had the option to use AI support for the next 45 min to complete the task, while also being able to seek guidance from their lecturer and tutor. In Session 13, students were assigned to develop their own R code based on the style and content of Experiment 3. They were permitted to use AI for this task and could also ask their lecturer or tutor for support. AI was chosen by 95% of the students.

2.2.1 Assessment of Self-Efficacy

Students completed online surveys at the end of each session. We compared the data from the third sessions of the Experiments 3 and 4, as, due to the curriculum, these sessions were similar. We used three versions of the Computer Self-Efficacy Measure Scale (Howard, 2014; Cronbach's $\alpha = .95$). To assess general computer skills at the beginning of Session 2, we translated Howard's scale and additionally used a single item (Tab. 1). Based on Howard's scale we adapted two additional scales to the R context. The scale RaSE we used in Session 10 and 13. The scale RaSE with AI support (RaSE+AI) we used in Session 12 before the implementation of AI and at the end of Session 13. It was a shortened form: We selected only five items that were most applicable to AI.

Tab. 1: Descriptive Statistics, Pearson Correlations, and Cronbach's Alpha vs. McDonald's Omega in the diagonal

Variables	Items	*M*	*SD*	1	2	3	4	5	6
1 Computer Self-Efficacy[ax]	11	3.01	0.63	α = .87 ω = .68					
2 "I rate my general computer skills as …"[ay]	1	2.98	0.86	.84***					
3 RaSE[bx]	11	2.64	0.63	.44***	.31*	α = .87 ω = .76			
4 RaSE[cx]	11	2.74	0.61	.54***	.41**	.71***	α = .88 ω = .79		
5 RaSE+AI[dx]	5	3.59	0.68	.41**	.36*	.17	.34*	α = .84 ω = .79	
6 RaSE+AI[cx]	5	3.37	0.77	.38**	.38**	.12	.42**	.66***	α = .96 ω = .93

Notes. Time of Assessment: [a]Beginning of Session 2, [b]End of Session 10, [c]End of Session 13, [d]Middle of Session 12.
Response options: [x]1 (*strongly disagree*) to 5 (*completely agree*). [y]1 (*very good*) to 5 (*very poor*).
Grey: Inferior model.
*p < .05, **p < .01, ***p < .001.

The two RaSE scales were distinguished by differences in item phrasing: “If I really make an effort, I can master difficult tasks in R, too.” (without AI) and “With AI support, I can master difficult tasks in R, too.” (with AI, Session 13, post-intervention). However, since students had no prior AI experience with R, pre-intervention (Session 12) phrasing had to reflect expectations, “With AI support, I think I can master difficult tasks in R, too.”

Cronbach’s α, based on our data, showed good to very good (retest)-reliability for all variations of the scales. For the scales computer self-efficacy and RaSE at both times of assessment, the congeneric model showed a superior fit, which led us to also calculate McDonald’s Omega (Tab. 1). These values we deemed mostly acceptable. Pearson correlations, as a sign of the convergent validity, were adequate (Tab. 1).

2.3 Design

We used a one-tailed dependent samples *t*-test to examine the effect of implementing AI on RaSE. Exploratively, we analyzed additional aspects to explain the first result, e.g. gender or RaSE+AI. The significance level was 5%.

3 Results

We analyzed the data with R (Version 4.4.1) including only data from students with complete assessments.

3.1. Hypothesis-testing Analysis

We found with a *t*-test no significant difference in RaSE before and after implementing AI, $\Delta = 0.10$; $t(56) = 1.64$, $p = .054$, $d = 0.22$, 95% CI [-0.05, 0.48]. The effect size *d* suggests a very small positive change in RaSE over time and students. Additionally, Fig. 3 displays student’s individual data progression.

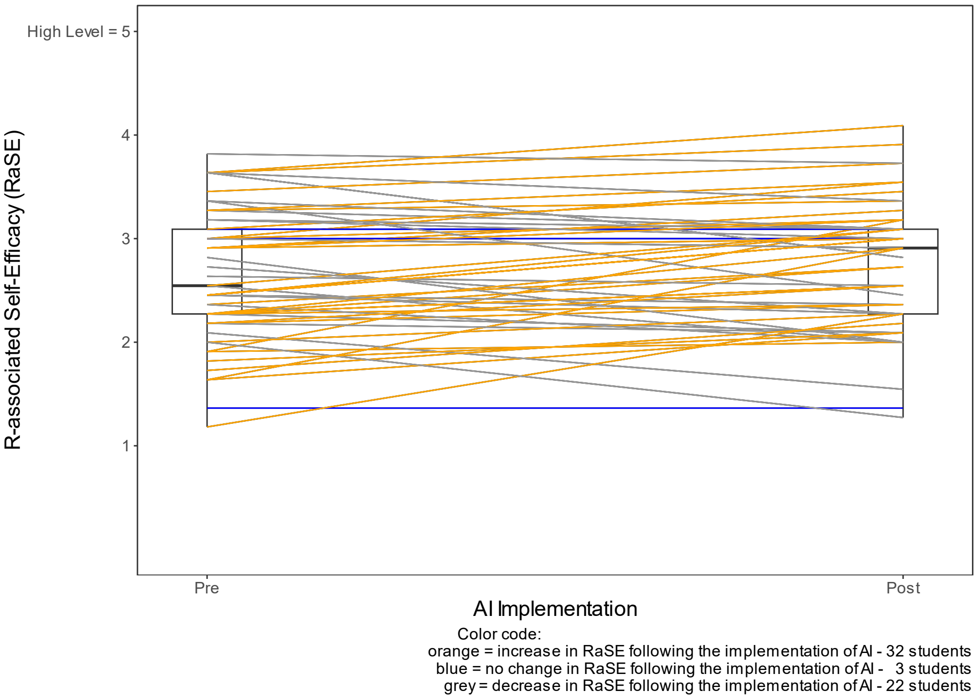

Fig. 3: Pre vs. Post RaSE

3.2 Explorative Analyses

To investigate this pattern, we incorporated additional variables. We conducted exploratory analyses of two sets of factors: 1) student- and seminar-related characteristics and 2) AI-related factors. These analyses were followed by two Analyses of Covariance. Finally, we examined RaSE+AI as the dependent variable. More details of these variables and analyses are provided in the supplementary material.

3.2.1 Student- and Seminar-Related Characteristics

In our investigation of characteristics, we examined with four two-way mixed Analyses of Variance gender, age category, variations in the five seminar groups, and students' self-assessed prior experience with R. These four analyses did not yield any significant results.

3.2.2 AI-related Factors

We also examined with four two-way mixed Analyses of Variance factors that could be subsumed under acceptance of AI or prior experience with AI: General prior usage of ChatGPT, prior usage of ChatGPT in R, prior usage of other AI tools, and apprehension about recent AI development. We also found no significant results.

3.2.3 Digital Literacy as Covariate

Furthermore, we examined with two Analysis of Covariances the influence of two covariates, which also proved to be non-significant: RaSE in conjunction with 1) general computer skills and 2) RaSE+AI.

3.2.4 Change of Dependent Variable

As a final option, we explored RaSE+AI as the dependent variable, leading to a significant t-test result, $\Delta = -0.24$; $t(56) = -2.97$, $p = .004$, $d = -0.39$, 95% CI [-0.66, -0.12] (Fig. 4). However, the effect size d suggests a small unexpected negative change in RaSE+AI over time and students. Given the 11 exploratory tests, a Bonferroni correction was necessary. Nonetheless, the result stayed significant.

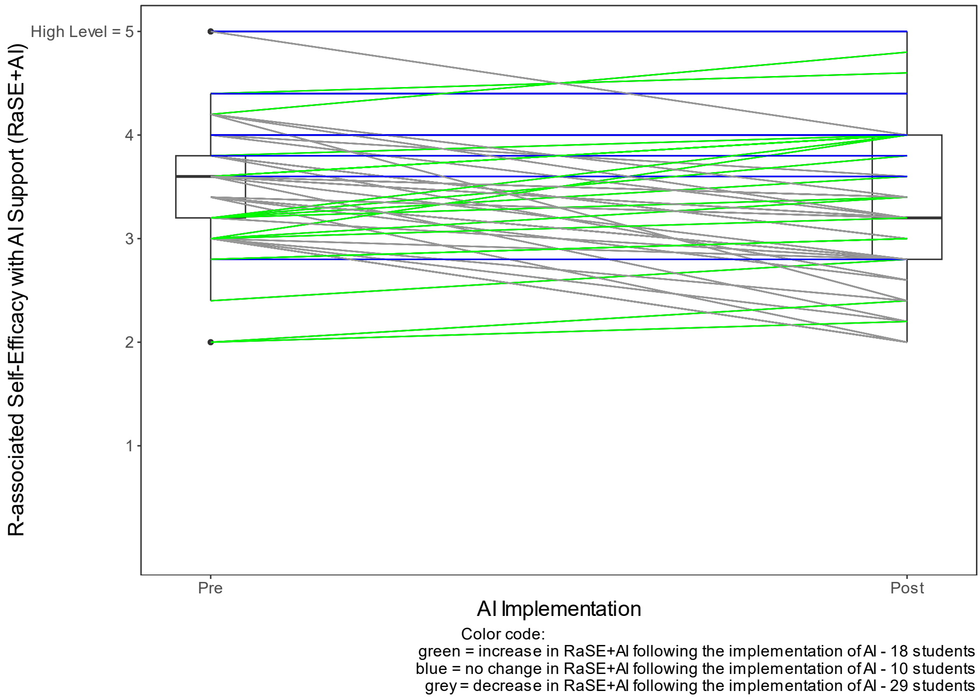

Fig. 4: Pre vs. Post RaSE+AI

4 Discussion

In this study, we examined the effect of implementing AI on psychology students' RaSE and found mostly non-significant results. Still, these results require careful interpretation due to the complex interplay of factors that influence students' RaSE.

In our main analysis we found no significant increase in students' mean RaSE after implementing AI. The lack of significant change can indicate that a semester of 13 sessions of using R for data analyses, including two sessions of AI, was insufficient to substantially alter students' RaSE.

In general, it takes time and practice to master any skill, e.g. coding (Newell & Rosenbloom, 1981). Our timeframe may have been too short to effectively implement new tools and significantly boost students' RaSE, particularly in autonomous R coding skills beyond prior levels.

However, a close examination of the individual data in Fig. 3 revealed a more nuanced picture. While 56% of the students reported at least slight improvements in RaSE, the other students reported a reduced or stable RaSE. We believe this different reaction pattern suggests that the effect of AI on RaSE can be influenced by individual or group differences.

4.1 Results of Explorative Analyses

To examine potential factors affecting this divergence, we conducted several exploratory analyses. We examined students' gender, considering the often-observed differences in STEM fields (Cheryan et al., 2017), and age categories to account for potential generational gaps in technology adoption (Prensky, 2009). While our age categories (18–22 and 23–44 years) are not traditional generational cohorts, the broader range in the older group can influence technology adoption through varied life experiences.

We also analyzed variations in seminar groups and lecturers, acknowledging the possible effect of teaching styles, group dynamics and student-lecturer relationships

(Hattie, 2008). We evaluated students' self-assessed prior experience with R and with AI to gauge the influence of existing skills (Hailikari et al., 2008). Additionally, we considered students' apprehensions about recent AI developments, recognizing that attitudes towards technology can effect engagement with it (Johnson & Verdicchio, 2017). We also included covariates such as general computer skills and RaSE+AI to control for digital competence (Sudaryanto et al., 2023).

Despite this comprehensive approach, none of these explorative analyses yielded statistically significant results. While the lack of significant findings across multiple factors suggests that the relationship between implementing AI and students' RaSE is more complex than we initially hypothesized, it also highlights some positive aspects. Notably, the absence of significant effects for gender, seminar group, and age category indicates that the effect of implementing AI in our study was relatively uniform across these characteristics. This suggests a certain level of equity in how students with different backgrounds interact with and benefit from AI tools.

It is possible that these factors interact in subtle ways not captured by our data, or that other unassessed variables play a crucial role. This lack of significant results emphasizes the need for more nuanced research approaches in future studies, while also suggesting that implementing AI in educational settings can have the potential to provide relatively equitable benefits between different students.

Building on these explorative analyses, we found an intriguing result when examining RaSE+AI as the dependent variable. This analysis yielded a significant result. However, the direction of this effect contradicted our expectation that RaSE+AI should increase after implementing AI. We ascribe this contradiction to the framing of our items across different sessions. In Session 12, items were formulated to capture students' expectations of AI support, while the items in Session 13 were designed to assess actual experiences. This shift in framing likely influenced students' assessment of their RaSE+AI. In contrast, we used in RaSE always the same items.

This result aligns with Gartner's hype cycle (1995), suggesting a phase of regret following inflated expectations, possibly triggered by media coverage. Fig. 4 reveals a slightly different pattern to Fig. 3: Only 32% of the students showed an increased

RaSE+AI after implementing AI compared to the previous 56%. We were unable to determine whether these groups resulted from individual challenges such as lack of objective skills or language difficulties (Nelson-Le Gall, 1985; Yilmaz & Yilmaz, 2023) due to the anonymous nature of the data.

4.2 Strength and Limitations

We must admit that our results were limited by the small sample size and, hence, reduced statistical power. This constraint arose from the field nature of our study and the students' voluntary partaking, factors we could not modify without compromising our study's validity. The rapid development of AI tools made it impractical to analyze data from multiple years to enhance sample size. Such a solution will likely introduce confounding variables due to the fast evolution of AI tools and changing students' prior experience with AI.

Another major limitation is the absence of a control group. However, such a control group was not feasible, as in our program all students are required to learn the same content.

Despite these limitations, we have chosen to publish this data for several reasons. First, we believe that our approach of implementing AI starting with an R script containing errors is valuable and innovative. This method provides a realistic scenario for students to engage with AI, mimicking debugging situations. Secondly, our result that two sessions are not sufficient for students to boost RaSE is a crucial information for other lecturers. This insight suggests the need for earlier and more extensive AI implementation in future curricula.

4.3 Practical Implications and Future Research

Implementing AI into R instruction presents several challenges. The multiplicity of approaches in statistics and R coding, particularly in data management, makes it difficult to develop a unified teaching approach. Furthermore, general seminar group sizes pose a substantial pedagogical challenge in providing individualized instruction whilst sustaining coherent group learning experiences.

These multi-faceted challenges underline the need for innovative pedagogical strategies to effectively implement AI into R instruction while also ensuring that students do not feel overwhelmed by AI and addressing potential negative perceptions. The decision to implement AI in our research seminar was driven by several factors, including the growing interest among students and lecturers for using AI tools in learning processes. Moreover, we respond to the increasing societal and academic pressure to engage with AI tools, recognizing that ignoring AI is no longer an option in higher education.

We implemented AI to provide students with practical experience, thereby hopefully enhancing their learning outcomes, and preparing them for the future and for autonomous coding. This approach aligns with professional demands, where AI proficiency is becoming increasingly valuable.

However, we recognize the importance of a careful approach to ensure that students do not become overly reliant on AI tools, potentially compromising valuable learning experiences (Darvishi et al., 2024). It is reassuring that our results and unsystematic observations in subsequent seminars have not yet indicated such a shortcut behavior. From the perspective of psychology as a subject, if students obtain correct solutions to problems and receive support in developing appropriate thinking strategies through AI support (Yilmaz & Yilmaz, 2023), this is not inherently problematic. Our primary objective is not to transform psychology students into professional coders but to develop their skills for addressing underlying psychological research questions. Our main goal is to ensure that students verify the correctness of AI-generated solutions.

While we examined in this study specifically R in the context of psychology, the insights gained can be used in other coding courses across various disciplines. The benefits and challenges are likely to be similar across different coding languages. Consequently, lecturers of other subjects can potentially adapt this approach to boost students' coding-related self-efficacy in their courses.

In future research, effects of implementing AI in multiple sessions or individual factors influencing students' adjustment to such AI tools can be explored. Ultimately, this study contributes to the scientific dialogue on balancing AI support with traditional teaching methods, particularly in disciplines where coding is not the focus but rather a necessary tool.

4.4 Conclusion

Whilst we did not find a significant short-term effect of implementing AI on students' RaSE in our study, we laid a useful basis for future research and practical considerations for evolving AI-supported education. Our results suggest that two AI-supported R coding sessions are insufficient to substantially alter students' self-assessment of their RaSE. This highlights the need for a more extended method to implement AI in seminar curricula.

The unexpected trend in RaSE+AI emphasizes the importance of managing students' expectations and experiences with new tools. Despite limitations, this study offers valuable insights for lecturers. Early guided AI implementation and balancing human and AI support are emphasized, especially in teaching data analysis.

In long-term studies the sustained effects of implementing AI on RaSE and actual coding proficiency can be explored. Examining individual factors influencing students' adjustment to AI tools can provide insights for personalized learning approaches. Additionally, comparative studies across different disciplines can shed light on how the effect of implementing AI varies depending on the subject context.

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6 Supplementary Materials

Additional materials are available at https://osf.io/uqm89.

References

Bühner, M. (2023). Zur Lage der Psychologie [The status of psychology]. *Psychologische Rundschau*, *74*(1), 1–20. doi.org/10.1026/0033-3042/a000616

Cheryan, S., Ziegler, S. A., Montoya, A. K., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others? *Psychological Bulletin*, *143*(1), 1–35. doi.org/10.1037/bul0000052

Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers & Education*, *210*, Article 104967. doi.org/10.1016/j.compedu.2023.104967

Elias, S. M., & MacDonald, S. (2007). Using past performance, proxy efficacy, and academic self-efficacy to predict college performance. *Journal of Applied Social Psychology*, *37*(11), 2518–2531. doi.org/10.1111/j.1559-1816.2007.00268.x

Garrel, J. von, Mayer, J., & Mühlfeld, M. (2023). *Künstliche Intelligenz im Studium: Eine quantitative Befragung von Studierenden zur Nutzung von ChatGPT & Co. [Artificial Intelligence in academia: A quantitative survey of students' use of ChatGPT & Co.]*. University of Applied Sciences Darmstadt. doi.org/10.48444/H_DOCS-PUB-395

Gartner. (2021, January 4). *Magic quadrant for network firewalls*. Gartner. https://www.gartner.com/en/documents/3887767

Hailikari, T., Katajavuori, N., & Lindblom-Ylanne, S. (2008). The relevance of prior knowledge in learning and instructional design. *American Journal of Pharmaceutical Education*, *72*(5), Article 113. www.ncbi.nlm.nih.gov/pmc/articles/PMC2630138

Hattie, J. (2008). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*. Routledge. doi.org/10.4324/9780203887332

Howard, M. C. (2014). Creation of a Computer Self-Efficacy Measure: Analysis of internal consistency, psychometric properties, and validity. *Cyberpsychology, Behavior, and Social Networking*, *17*(10), 677–681. doi.org/10.1089/cyber.2014.0255

Johnson, D. G., & Verdicchio, M. (2017). AI anxiety. *Journal of the Association for Information Science and Technology*, *68*(9), 2267–2270. doi.org/10.1002/asi.23867

Macher, D., Paechter, M., Papousek, I., Arendasy, M., Ruggeri, K., & Freudenthaler, H. (2013). Statistics anxiety, state anxiety during an examination, and academic achievement. *British Journal of Educational Psychology, 83(*4*), 535–549*. doi.org/10.1111/j.2044-8279.2012.02081.x

Narciss, S. (2020). Feedbackstrategien für interaktive Lernaufgaben [Feedback strategies for interactive learning tasks]. In H. Niegemann & A. Weinberger (eds.), *Handbuch Bildungstechnologie* (pp. 369–392). Springer Berlin Heidelberg. doi.org/10.1007/978-3-662-54368-9_35

Nelson-Le Gall, S. (1985). Chapter 2: Help-seeking behavior in learning. *Review of Research in Education*, *12*(1), 55–90. doi.org/10.3102/0091732X012001055

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of skill acquisition and the Law of Practice. In *Cognitive skills and their acquisition* (pp. 1–55). Routledge. doi.org/10.4324/9780203728178

Prensky, M. (2009). H. sapiens digital: From digital immigrants and digital natives to digital wisdom. *Innovate: Journal of Online Education*, *5*(3). Article 104264. www.learntechlib.org/p/104264

Ramalingam, V., & Wiedenbeck, S. (1998). Development and validation of scores on a Computer Programming Self-Efficacy Scale and group analyses of novice programmer self-efficacy. *Journal of Educational Computing Research*, *19*(4), 367–381. doi.org/10.2190/C670-Y3C8-LTJ1-CT3P

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. doi.org/10.1037/0003-066X.55.1.68

Schunk, D. H., & Pajares, F. (2002). The development of academic self-efficacy. In *Development of Achievement Motivation* (pp. 15–31). Elsevier. doi.org/10.1016/B978-012750053-9/50003-6

Sudaryanto, M. R., Hendrawan, M. A., & Andrian, T. (2023). The effect of technology readiness, digital competence, perceived usefulness, and ease of use on accounting students Artificial Intelligence technology adoption. *E3S Web of Conferences*, *388*, Article 04055. doi.org/10.1051/e3sconf/202338804055

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, *49*(3), 33–35. doi.org/10.1145/1118178.1118215

Yilmaz, R., & Yilmaz, F. G. K. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence*, *4*, Article 100147. doi.org/10.1016/j.caeai.2023.100147