Please quote as: Ritz, E. (2024). Balancing Bytes with Brains: Exploring the Role of Learners' Control in Personalized Learning Tasks. *European Conference on Information Systems*, Paphos, Cyprus.

BALANCING BYTES WITH BRAINS: EXPLORING THE ROLE OF LEARNERS' CONTROL IN PERSONALIZED LEARNING TASKS

Short Paper

Eva Ritz, University of St. Gallen, St.Gallen, Switzerland, eva.ritz@unisg.ch

Abstract

The increasing prevalence of artificial intelligence (AI)-based learning systems unleashes new potentials in designing personalized learning experiences that enhance learning outcomes. However, prior research indicates that such systems can negatively impact engagement due to issues in human information processing. This study examines whether giving learners control over task difficulty selection in personalized learning systems can mitigate these effects. A laboratory within-subjects experiment involving 80 participants explored how control over personalized vocabulary learning affects learning performance and autonomy satisfaction. As such a control feature may lead to deeper information processing, I investigate the mediating effect of cognitive workload on the main effect. The study aims to contribute to human-AI interaction literature by shedding light on the importance of control in personalized system design and investigating its effects on cognitive workload, overall task performance, and autonomy satisfaction.

Keywords: Personalized Learning, Autonomy, EEG, Cognitive Load Theory.

1 Introduction

Digital learning systems today have the potential to revolutionize education by fostering personalized and interactive learning journeys, monitoring performance, and offering tailored assessments and feedback (Ritz and Grueneke, 2022). The promise of personalization processes according to the learners' personality, knowledge level, or preferences promises to enhance their attention, behavior, and outcomes while reducing dropout rates in online courses (Greller and Drachsler, 2012). This approach is grounded in constructivist research, which embraces the notion of "multiple realities" and posits that learners necessitate individualized guidance based on their experiences to achieve optimal learning outcomes (Vygotsky, 1980). Hence, it underscores the rationale behind the efficacy of personalized learning tasks in augmenting learning performance. While the first generation of conventional learning management systems was traditionally designed to assist human educators (e.g., by providing additional learning materials), artificial intelligence (AI)-based learning systems nowadays possess the autonomy to adapt to users and take over the role of a teacher to track knowledge and provide personalized learning activities (Abdelrahman et al., 2023). For instance, the widespread learning application Duolingo personalized language learning in the form of small-scale vocabulary tasks.

Despite the potential of such applications, prior research has found adverse effects on human information processing (Tam and Ho, 2006). Humans generally tend to minimize cognitive effort and, thus, tend to adopt intuitive conclusions without effort thinking (Kim et al., 2019). For instance, existent literature uncovered that users supported by intelligent tools frequently rely on the systems' advice due to a lack of cognitive processing (Fügener et al., 2021). In the context of learning, such a phenomenon may negatively impact learner's outcomes (Li and Little, 2023). Cognitive load theory by Sweller (2011) is an extension of information processing, focusing on short-term working memory capacity limitations.

Literature from human-computer interaction found that users of information technology tend to rely on external tools to reduce their working memory load and thereby unlock mental resources for different, more complex tasks (Lodge et al., 2023). This phenomenon can lead to beneficial effects, such as task speed or accuracy, but it also diminishes learner's abilities and memory (Grinschgl et al., 2021). Based on the authors' study, adverse effects can be reduced by increasing the efforts of offloading (Grinschgl et al., 2021).

What if personalized learning tasks were adaptable for learners based on their difficulty preferences? Giving learners self-control over their personalized learning tasks can increase their satisfaction and outcomes (Schneider et al., 2018). Accordingly, learners with control over their personalization will expend more significant cognitive effort to consider their task difficulty level, deepening their cognitive effort. Thus, I ask *how providing learners with control over their personalized learning tasks influences learning performance and autonomy satisfaction*.

To answer the research question, I conduct a laboratory within-subject experiment with manipulations of personalization and degree of control in language learning tasks. I use electroencephalography (EEG) for continuous cognitive load measurements with a specific focus on the frontal cortex regions. Previous research has found that EEG is promising for continuous load measurements and, therefore, increases the internal validity of this study (Antonenko et al., 2010). With this experiment, I aim to contribute to human-AI interaction literature by shedding light on the importance of control in personalized learning tasks and investigating its effects on cognitive workload, overall performance, and autonomy satisfaction.

2 Theoretical Background and Hypothesis Development

2.1 Effects of personalized learning on learning performance

The personalization of learning paths has always been a significant phenomenon of study in pedagogical research. The prevailing view remains that acquiring new knowledge is most efficient with a personalized instructor (Oda et al., 2014). While personalization of a learning path can be conducted based on various parameters, such as the learners' personality, preferences, or knowledge level (Ritz et al., 2024), this research focuses on the personalization of learning tasks according to the learner's previous knowledge. One prevalent theoretical concept in that regard, and the predecessor of personalized learning, is the zone of proximal development. The theory posits that for an optimal learning experience, tasks and instructions should be scaffolded just outside the learners' current ability (Vygotsky, 1980).

While traditional classroom education in the past failed to offer such personalized guidance due to time and organizational constraints, the rise of digital learning systems along with novel data science techniques promised new possibilities to leave behind the one-size-fits-all mentality (Brinton et al., 2015; Ritz et al., 2022). Research on the integration of AI in learning systems can be traced back to a study by Beck et al. (1996) which was among the first to apply AI in the educational domain. Since then, research on this topic has witnessed continuous development along with the advances made in the field of AI. Kaplan and Haenlein (2019, p. 15) conceive AI as "*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption*". AI-based learning systems cannot only support learners with learning content but also act autonomously and learn based on the user's data. This also implies that the system can implement its own interventions and decisions without the influence of an instructor or learner (Walsh et al., 2021). While the personalization of learning tasks has been investigated during the last decades and expects a positive effect on learning performance (Huang et al., 2023), González-Calatayud et al. (2021, p.12) endorse that *"the possibilities that AI offers to education are enormous, especially for tutoring, assessment, and personalization* of *education, and most of these are yet to be discovered."* A study of Ferguson et al. (2022) found that personalized educational games recommended according to the concept of the zone of proximal development improve learning performance. Therefore, I hypothesize:

Hypothesis 1: Learners with personalized learning tasks will have higher learning performance than learners without personalization.

Cognitive load theory is based on our human cognition and posits that the human working memory human working memory is the central bottleneck in the acquisition of knowledge (Sweller, 2011). From a neuroscientific perspective, the cognitive load is compelled by the working memory (Wang et al., 2016). The instructional design of educational resources offline and online (such as the task recommended by the system) influences this load. Hence, it explains the level of resources used when an individual completes a learning task. Research suggests that personalized learning may reduce cognitive workload (for instance, Mo et al. (2022)) but also leads to offloading behavior (Grinschgl and Neubauer, 2022) in which learners reduce their cognitive effort in thinking about their own knowledge and abilities. This might weaken the main positive effect on learning performance (hypothesis 2).

Hypothesis 2: The relationship between learners' personalization on learning performance is mediated by the degree of cognitive load.

Learner's control generally refers to the possibility of learners exercising a level of control over the instructed events (Simsek, 2012). As current digital learning solutions, such as massive open online courses or mobile-based learning apps, on the market offer limited potential for learners to take control of the learning process, I investigate this factor, implying that the learner can select suitable task difficulty levels. Prior research found evidence that self-control and partial self-control of task difficulty promote skill learning (Andrieux et al., 2016). A study by Couvillion et al. (2020) explains that giving learners self-control leads to deeper information processing, as they are allowed to make choices during their practice. Hence, this study aims to investigate this effect using EEG-based continuous cognitive load measurements.

Hypothesis 3: The level of control moderates the indirect effect of personalization on learning performance through the degree of cognitive load.

2.2 Effects of personalized learning on autonomy satisfaction

In addition, research suggests that personalization and self-control influence autonomy satisfaction. Based on self-determination theory in the context of learning, learners with perceived autonomy support (for instance, from a teacher or a learning system) can receive higher satisfaction with their autonomy. Prior research found that found that students with high autonomy satisfaction positively influenced their engagement, finally affecting their academic accomplishments (Jang et al., 2010; Gutiérrez et al., 2018). A high degree of self-control in the learning system during the choice of task difficulty level as autonomy support gives learners the opportunity to reflect on their achievements positively influences their autonomy satisfaction.

Hypothesis 4: Learners in the applied self-control condition will have higher levels of autonomy satisfaction than learners without control.

3 Research Method

3.1 Experimental design

I compare the neurophysiological cognitive load measurements across all experimental conditions. Due to the non-comparability of brain structures between individuals (Moravec et al., 2022), I opt for a within-subject design. I conduct a 2x2 factorial design to test the posed hypotheses, yielding four distinct experimental conditions (see Figure 1).

The first factor is “personalization”: According to the concept of the zone of proximal development, participants received a task with higher difficulty level if they answered a question correct and a lower difficulty level if they answered incorrectly. Thereby, I follow an approach like Sampayo-Vargas et al. (2013). Our personalization approach mimics an AI-based approach by following heuristic rules. Participants get personalized tasks based on whether they answered the task correctly or not. For the first task difficulty, they initially undergo a self-assessment, serving as a baseline for selecting the initial task difficulty level (following the approach of Yazidi et al., 2020). The second factor is “control”: Participants with applied control get to choose the difficulty levels of each vocabulary task themselves.

		Personalization	
		None	**Applied**
Control	**None**	**Condition 1: Control condition** • Neither manipulations are applied • Participants receive randomly picked tasks from the learning system	**Condition 3: Applied Personalization condition** • Personalization manipulation is applied • Participants receive personalized tasks from the learning system
	Applied	**Condition 2: Applied Control condition** • Control manipulation is applied • Participants must select the task difficulty of the next task without advice from the system	**Condition 4: Applied Personalization + control condition** • Both manipulations are applied • Participants receive a personalized recommendation from the learning system and can select to follow or overrule it

Figure 1. Experimental conditions.

In the “control condition” (condition 1), where none of the factors are applied, participants receive tasks at random difficulty levels selected by the system, meaning that the tasks are not chosen according to the participants’ difficulty level. In the “applied control” condition (condition 2), learners possess the control to self-select task difficulty levels within the learning system. Subjects in the “applied personalization” condition (condition 3) received personalized learning tasks suitable for the individual from the system. In the “applied personalization + control” condition (condition 4), learners receive a recommendation of the suitable task difficulty level and retain the choice to either adhere to the system's suggestion or override by self-selecting their preferred difficulty level. Participants engage in all four experimental conditions, as depicted in Figure 2. After each condition, they fill out a post-survey to evaluate autonomy satisfaction.

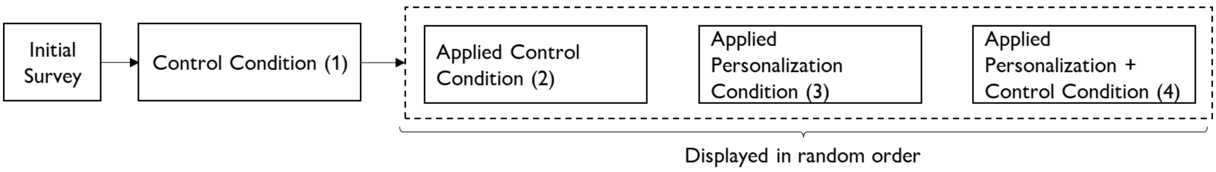

Figure 2. Experimental procedure.

3.2 Tasks

Participants receive vocabulary translation tasks for three main reasons: First, vocabulary tasks have pre-defined difficulty levels according to the common framework of reference for languages (François et al., 2014). Second, while the task difficulty varies based on the personalization algorithm, the task complexity remains relatively stable for all tasks. Third, the short duration of the tasks leads to the extraction of short EEG time epochs to improve EEG interpretation. The time of task completion ranged from 0.58 seconds to 250.19 seconds, with a mean of 8.30 seconds per vocabulary translation task. The French-English translation was chosen because French is the fifth most-spoken language in the world and one of the country's four official languages, allowing for a heterogeneous sample of participants regarding their language skills. For each condition, participants must translate 20 vocabularies from French into English, adding up to 80 vocabulary translation tasks. Each vocabulary item is asked only once per participant to minimize learning effects during vocabulary training. Participants always needed to provide an answer, and they were not able to skip a translation task.

3.3 Participants

Participants were recruited through a student pool of a public Swiss University. Our participant pool comprises 80 individuals, with exclusion criteria encompassing left-handedness due to differing brain structures (Moravec et al., 2022). Participants were required to have a profound understanding of the English language. Regarding gender, 44,2 percent of participants identify as female, 55,8 percent of participants identify as male, and zero percent of participants identify as non-binary or do not want to disclose their gender. 33.3 percent of participants enclosed that they received a high school diploma as the highest educational degree, 8.6 percent stated their highest degree is a university without a degree, 32.1 percent received a bachelor's degree, 19.8 percent of the sample finished their master's degree, and 1.2 percent of participants obtained a professional degree as their highest educational degree. The mean age of the participants was 23.593 years.

3.4 Measures

Cognitive load. Based on previous studies, the focus for cognitive load measurements is on alpha activities (Minas et al., 2014; Wang et al., 2016). I follow the measurement method based on Klimesch (1999). The neurophysiological measurements enable the investigation of continuous measurements (Yoo et al., 2023) instead of self-reported questionnaires after each vocabulary task, which might improve the ecological validity of the study.

Autonomy satisfaction. The construct is based on the basic psychological need satisfaction and frustration scale for adults in English, including four items, such as "I feel a sense of choice and freedom in the task I have undertaken". The items were measured on a 7-point Likert scale (Deci and Ryan, 2000; Brenning et al., 2019).

Learning performance. The number of correctly answered vocabulary questions is divided by the total number of vocabulary questions for each condition (Fügener et al., 2021).

3.5 Neurophysiological data analysis

The EEG data was collected using the consumer-grade Emotiv EPOC device with 14 channels, which has been previously used in leading IS journals. Consumer-grade devices nowadays gain broader attention and acceptance, especially for time-frequency brainwave analysis (for more details see Riedl et al., 2020). At the present stage, the project engages in analyzing the EEG data for the cognitive load measurement, employing EEGLab—an established open-source toolbox for EEG analysis (Delorme and Makeig, 2004). For the analysis, I will follow the principles of Minas et al. (2014) and Kim et al. (2019). First, eye movement and muscle artifacts are removed using EEGLab probability calculations and visual inspection. Second, the data is analyzed using independent components analysis decomposition, which can isolate independent components of activation. Third, event-related spectral perturbation (ERSP) is conducted to model time and frequency changes that occur in individual components over specified time windows (for each vocabulary task). Since the alpha frequency, between 8-13 Hz, is closely related to cognitive load, I focus on generating ERSPs including alpha frequency.

4 Preliminary Results

I first conducted confirmatory factor analysis for construct validation. Cronbach's alpha (C(α)) of the autonomy satisfaction construct suggests a good reliability of the factor for measurements on all four conditions (C(α) for AUSAT_1 = 0.8291991, C(α) for AUSAT_2 = 0.8280994, C(α) for AUSAT_3 = 0.8349826, C(α) for AUSAT_4 = 0.8793258).

Descriptive statistics suggest that the type of personalization affects learning performance. On average, learning performance is higher in the "applied personalization" condition (0.51%) than in the control condition (0.49%) learning performance. The standard deviation (ST) of the learning performance is highest in the "applied control" condition (SD = .15) and smaller in the "applied personalization" condition (SD = .07). A paired-sample t-test with learning outcome as the dependent variable and personalization as a factor was conducted to get the first results for hypothesis 1. To test for the assumption of normal distribution for the paired samples t-test, I performed a Shapiro-Welk test (p = .35) that did not show evidence of non-normality (Shapiro and Wilk, 1965). However, the paired-sample t-test found no significant differences between the conditions with respect to the learning performance (t (80) = -1.58, p = .13). The moderated mediation analysis (H1-4) will be performed using PROCESS (Hayes, 2013).

Regarding the effects on autonomy satisfaction (H5), descriptive statistics reveal that the control factor affects autonomy satisfaction. On average, autonomy is higher in the "applied control" condition (M = 3.56, SD = 1.24) than in the "control" condition (M =3.24, ST = 1.28). The Shapiro-Wilk test suggests that the data is normally distributed (p = .21). A paired-sample t-test confirms significant differences between the conditions on autonomy satisfaction (t(76) = -2.92, p = .004).

5 Next Steps, Limitations, and Future Outlook

Concerning the progress of the experimental study, the data collection and pre-processing are complete. The next steps for hypothesis testing are the EEG main data analysis and the main hypothesis testing of the moderated mediation effect.

This research-in-progress study has several limitations. First, due to conceptualization in general, our preliminary findings for a particular learning system and vocabulary training context cannot be generalized to different experimental settings. Future research could, for instance, address personalized learning with a generative AI, whose communication is, per se, controlled by the user through prompts. Second, although the tasks were categorized according to pre-defined difficulty levels, there might be insignificant differences in task difficulty and complexity (e.g., by varying word length). To minimize such effects and increase the stability of task difficulty and complexity, natural language processing methods could be applied in the personalization algorithm to recommend similar words in terms of length, difficulty, and other factors.

In conclusion, this experiment aims to illuminate the importance of control in personalized learning tasks and investigate its effects on cognitive workload, overall task performance, and autonomy satisfaction. Further, this study aspires to provide practical insights for massive open online course providers and educational designers who apply personalized learning algorithms and might struggle with unengaged interaction.

References

Abdelrahman, G., Wang, Q. and Nunes, B. (2023). "Knowledge Tracing: A Survey." *ACM Computing Surveys*, *55*(11), 1–37.

Andrieux, M., Boutin, A. and Thon, B. (2016). "Self-Control of Task Difficulty During Early Practice Promotes Motor Skill Learning." *Journal of Motor Behavior*, *48*(1), 57–65.

Antonenko, P., Paas, F., Grabner, R. and van Gog, T. (2010). "Using Electroencephalography to Measure Cognitive Load." *Educational Psychology Review*, *22*(4), 425–438.

Beck, J., Stern, M. and Haugsjaa, E. (1996). "Applications of AI in education." *XRDS: Crossroads, The ACM Magazine for Students*, *3*(1), 11–15.

Brenning, K., Soenens, B., Mabbe, E. and Vansteenkiste, M. (2019). "Ups and Downs in the Joy of Motherhood: Maternal Well-Being as a Function of Psychological Needs, Personality, and Infant Temperament." *Journal of Happiness Studies*, *20*(1), 229–250.

Brinton, C. G., Rill, R., Ha, S., Chiang, M., Smith, R. and Ju, W. (2015). “Individualization for Education at Scale: MIIC Design and Preliminary Evaluation.” *IEEE Transactions on Learning Technologies*, *8*(1), 136–148.

Couvillion, K. F., Bass, A. D. and Fairbrother, J. T. (2020). “Increased cognitive load during acquisition of a continuous task eliminates the learning effects of self-controlled knowledge of results.” *Journal of Sports Sciences*, *38*(1), 94–99.

Deci, E. L. and Ryan, R. M. (2000). “The “What” and “Why” of Goal Pursuits: Human Needs and the Self-Determination of Behavior.” *Psychological Inquiry*, *11*(4), 227–268.

Delorme, A. and Makeig, S. (2004). “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis.” *Journal of Neuroscience Methods*, *134*(1), 9–21.

Ferguson, C., van den Broek, E. L. and van Oostendorp, H. (2022). “AI-Induced guidance: Preserving the optimal Zone of Proximal Development.” *Computers and Education: Artificial Intelligence*, *3*, 100089.

François, T., Gala, N., Watrin, P. and Fairon, C. (2014). “FLELex: a graded lexical resource for French foreign learners.” in: *9th International Conference on Language Resources and Evaluation*. Reykjavik, Iceland.

Fügener, A., Grahl, J., Gupta, A. and Ketter, W. (2021). “Will humans-in-the-loop become borgs? Merits and pitfalls of working with AI.” *MIS Quarterly*.

González-Calatayud, V., Prendes-Espinosa, P. and Roig-Vila, R. (2021). “Artificial Intelligence for Student Assessment: A Systematic Review.” *Applied Sciences*.

Greller, W. and Drachsler, H. (2012). “Translating Learning into Numbers: A Generic Framework for Learning Analytics.” *Educational Technology & Society*, *15*(3), 42–57.

Grinschgl, S. and Neubauer, A. C. (2022). “Supporting Cognition With Modern Technology: Distributed Cognition Today and in an AI-Enhanced Future.” *Frontiers in Artificial Intelligence*, *5*.

Grinschgl, S., Papenmeier, F. and Meyerhoff, H. S. (2021). “Consequences of cognitive offloading: Boosting performance but diminishing memory.” *Quarterly Journal of Experimental Psychology*, *74*(9), 1477–1496.

Gutiérrez, M., Sancho, P., Galiana, L. and Tomás, J. M. (2018). “Autonomy Support, Psychological Needs Satisfaction, School Engagement and Academic Success: A Mediation Model.” *Universitas Psychologica*, *17*(5), 1–12.

Hayes, A. F. (2013). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. London & New York: Guilford Press.

Huang, A. Y. Q., Lu, O. H. T. and Yang, S. J. H. (2023). “Effects of artificial Intelligence–Enabled personalized recommendations on learners’ learning engagement, motivation, and outcomes in a flipped classroom.” *Computers & Education*, *194*.

Jang, H., Reeve, J. and Deci, E. L. (2010). “Engaging students in learning activities: It is not autonomy support or structure but autonomy support and structure.” *Journal of Educational Psychology*, *102*(3), 588–600.

Kaplan, A. and Haenlein, M. (2019). “Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence.” *Business Horizons*, *62*(1), 15–25.

Kim, A., Moravec, P. L. and Dennis, A. R. (2019). “Combating Fake News on Social Media with Source Ratings: The Effects of User and Expert Reputation Ratings.” *Journal of Management Information Systems*, *36*(3), 931–968.

Klimesch, W. (1999). “EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis.” *Brain Research Reviews*, *29*(2–3), 169–195.

Li, M. D. and Little, B. P. (2023). “Appropriate Reliance on Artificial Intelligence in Radiology Education.” *Journal of the American College of Radiology*.

Lodge, J. M., Yang, S., Furze, L. and Dawson, P. (2023). “It’s not like a calculator, so what is the relationship between learners and generative artificial intelligence?” *Learning: Research and Practice*, *9*(2), 117–124.

Minas, R. K., Potter, R. F., Dennis, A. R., Bartelt, V. and Bae, S. (2014). "Putting on the Thinking Cap: Using NeuroIS to Understand Information Processing Biases in Virtual Teams." *Journal of Management Information Systems*, *30*(4), 49–82.

Mo, C.-Y., Wang, C., Dai, J. and Jin, P. (2022). "Video Playback Speed Influence on Learning Effect From the Perspective of Personalized Adaptive Learning: A Study Based on Cognitive Load Theory." *Frontiers in Psychology*, *13*.

Moravec, P. L., Kim, A., Dennis, A. R. and Minas, R. K. (2022). "Do You Really Know if It's True? How Asking Users to Rate Stories Affects Belief in Fake News on Social Media." *Information Systems Research*, *33*(3), 887–907.

Oda, Y., Onishi, H. and Sakemi, T. (2014). "Effectiveness of Student Tutors in Problem-Based Learning of Undergraduate Medical Education." *The Tohoku Journal of Experimental Medicine*, *232*(3), 223–227.

Riedl, R., Minas, R. K., Dennis, A. and Müller-Putz, G. R. (2020). "Consumer-Grade EEG Instruments: Insights on the Measurement Quality Based on a Literature Review and Implications for NeuroIS Research." in: Davis, F. D., Riedl, R., vom Brocke, J., Léger, P. M., Randolph, A. B. (eds.), *Information Systems and Neuroscience*, 350-361, Springer.

Ritz, E., Freise, L. R., Elshan, E., Rietsche, R. and Bretschneider, U. (2024). "What to Learn Next? Designing Personalized Learning Paths for Re-&Upskilling in Organizations." in: *Proceedings of the 57th Hawaii International Conference on System Sciences*, 267–277. Honolulu, Hawaii.

Ritz, E. and Grueneke, T. (2022). "Learn Smarter, Not Harder – Exploring the Development of Learning Analytics Use Cases to Create Tailor-Made Online Learning Experiences." In *Proceedings of the 55th Hawaii International Conference on System Sciences,* Maui, Hawaii (Virtual).

Ritz, E., Wambsganss, T., Rietsche, R., Schmitt, A., Oeste-Reiss, S. and Leimeister, J. M. (2022). "Unleashing Process Mining for Education: Designing an IT-Tool for Students to Self-Monitor their Personal Learning Paths." in: *Wirtschaftsinformatik*.

Sampayo-Vargas, S., Cope, C. J., He, Z. and Byrne, G. J. (2013). "The effectiveness of adaptive difficulty adjustments on students' motivation and learning in an educational computer game." *Computers & Education*, *69*, 452–462.

Schneider, S., Nebel, S., Beege, M. and Rey, G. D. (2018). "The autonomy-enhancing effects of choice on cognitive load, motivation and learning with digital media." *Learning and Instruction*, *58*, 161–172.

Shapiro, S. S. and Wilk, M. B. (1965). "An analysis of variance test for normality (complete samples)." *Biometrika*, *52*(3–4), 591–611.

Simsek, A. (2012). "Learner Control." in: *Encyclopedia of the Sciences of Learning*, 1748–1750. Boston, MA: Springer US.

Sweller, J. (2011). "Cognitive Load Theory" (pp. 37–76).

Tam, K. Y. and Ho, S. Y. (2006). "Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes." *MIS Quarterly*, 865–860.

Vygotsky, L. S. (1980). *Mind in Society - Development of Higher Psychological Processes*.

Walsh, K. R., Mahesh, S. and Trumbach, C. C. (2021). "Rationalizing the Fears." *The Journal of Technology Studies*, *47*(1), 38–47.

Wang, S., Gwizdka, J. and Chaovalitwongse, W. A. (2016). "Using Wireless EEG Signals to Assess Memory Workload in the n-Back Task." *IEEE Transactions on Human-Machine Systems*, *46*(3), 424–435.

Yazidi, A., Abolpour Mofrad, A., Goodwin, M., Hammer, H. L. and Arntzen, E. (2020). "Balanced difficulty task finder: an adaptive recommendation method for learning tasks based on the concept of state of flow." *Cognitive Neurodynamics*, *14*(5), 675–687.

Yoo, G., Kim, H. and Hong, S. (2023). "Prediction of Cognitive Load from Electroencephalography Signals Using Long Short-Term Memory Network." *Bioengineering*, *10*(3), 361.