Artificial intelligence and education: Addressing the variability in learners' emotion and motivation with adaptive teaching assistants

Rebecca Lazarides / Johann Chevalère

Zusammenfassung: Eine zentrale Herausforderung für Lern- und Bildungsprozesse in modernen Gesellschaften ist es, die Heterogenität von Lernenden in den Blick zu nehmen und effektiv auf ihre individuellen Bedürfnisse bei der Wissensvermittlung einzugehen. Schüler*innen unterscheiden sich in ihren individuellen Lernmerkmalen, beispielsweise in ihrer Leistungsfähigkeit, ihrem Vorwissen, aber auch in ihrer Lernmotivation und ihren lernrelevanten Emotionen. Lehrkräfte haben häufig nur limitierte Ressourcen zur Verfügung, um allen Lernenden optimal auf ihre individuellen Bedarfe zugeschnittene Lerngelegenheiten zu bieten. Der vorliegende Beitrag befasst sich vor diesem Hintergrund mit künstlich intelligenten Lernbegleitern und ihrer Bedeutung für die Entwicklung adaptiver Lerngelegenheiten, die unterschiedliche Voraussetzungen und Bedürfnisse von Lernenden im Bereich Motivation und Emotion berücksichtigen.
Schlüsselbegriffe: Motivational-affektive Lernentwicklung, Intelligente Tutorielle Systeme, Lernroboter, Individualisiertes Unterrichten

Summary: One of the main challenges of education in modern societies is to effectively address the variability of students in academic learning settings. Students vary in terms of their individual learning preconditions, such as achievement and preknowledge, but also motivation and emotion. Teachers, in turn, have limited resources to provide each learner with individually tailored instruction. This research overview reviews research on artificially intelligent teaching assistants and their role in providing adaptive learning opportunities in relation to learners' heterogeneous individual learning preconditions in the field of motivation and emotion.
Keywords: Motivational-affective learning processes, Intelligent tutoring systems, social robots, individualized instruction

1. Adaptive teaching and artificial intelligence: addressing heterogeneous groups of students in classrooms

Classrooms in modern societies are characterized by a high diversity of learners – students differ greatly in their individual characteristics, such as gender, socio-economic background or language, but also in terms of their individual learning preconditions regarding, for example, performance, motivation, and emotion (Hachfeld / Lazarides 2020; McCombs 2010). Teachers face the challenge of addressing the needs of individual learners when planning and conceptualizing their materials, tasks, examples, and

Bildung und Erziehung 74. Jg., S. 264 – 279, ISSN (Printausgabe): 0006-2456, ISSN (online): 2194-3834

instructional settings, but also in their individual adaptive teaching behaviors, such as in instructional dialogues (Dumont 2019). Adaptive instruction is closely connected to the concept of scaffolding, which is defined as temporary teacher support for the completion of a task that students might not be able to complete, aiming to enable students to take responsibility for their own learning (Van de Pol et al. 2010). The concept refers to Vygotsky's (1978) "zone of proximal development" that describes the distance between the developmental level of independent problem solving and the potential development when social support and collaboration are provided. Although individualized learning support has been shown to be beneficial for students' perceived autonomy and competence and, through this, for their motivation (e.g., Rubach / Lazarides 2019), teachers often do not feel prepared to apply such teaching methods (Connor 2019). In the present research overview, we focus on the role of artificially intelligent teaching assistants as a means to support teachers in providing individualized instruction.

In a non-representative online survey with 320 participants in Germany, 'individualization and differentiation' was one of the most frequently stated perceived potentials of intelligent, artificial teaching assistants in education (Ballod / Klein 2020). In large classrooms, teachers often have time restrictions and limited attention, which makes it difficult to support each student individually (Hachfeld / Lazarides 2020). Artificial intelligence (AI) has the potential to address these difficulties and to assist teachers by reducing workload and supporting students through personalized learning (van der Vorst / Jelicic 2019). Personalized learning is a somehow fuzzy concept that is increasingly referred to in educational contexts, but the respective definition is vague (Walkington / Bernacki 2020). Broadly defined, personalization in education means processes of instruction that use information from or about an individual student to plan and design educational settings for this student (Beese 2019). In some cases, personalized learning also uses machine-learning algorithms to select adequate tasks and examples based on students' individual levels of ability and motivation (Ross et al. 2013). Using such new methodological approaches can enable teachers to focus their attention on students with specific needs, and enables students to learn at their own pace (van der Vorst / Jelicic 2019). A highly relevant research direction in this context is research on the role of adaptive learning systems such as Intelligent Tutoring Systems (ITS) in learning processes. ITS are computer-based learning environments that include a model of the student (e.g. current knowledge level), the expert (e.g., knowledge that needs to be conveyed and the difficulty level of specific tasks), and the instructional process (e.g. teaching methods tailored to specific students), and tailor learning content and instructional feedback to the learner. The models are successively developed further as students navigate through an interface that allows dynamic interactions with the system. Using ITS can support classroom instruction because multiple students can deal individually with similar tasks receiving personalized information and feedback about their learning progress. A meta-analysis of Ma et al. (2014) on the effectiveness of ITS in learning processes showed that the use of ITS was associated with greater achievement in comparison with teacher-led, large-group instruction, non-ITS computer-based instruction, and textbooks, but no significant differences occurred between learning from ITS and learning from individualized human tutoring or small-group instruction. Another review (Kulik / Fletcher 2016) reports moderate-to-large effect sizes for ITS effects on students' performance when comparing ITS with conventional classes. However, the effect sizes were much smaller when outcomes were measured with standardized tests instead of non-standardized performance measures.

A relatively new field in AI and adaptive instruction is the implementation of robot teaching assistants in class – either robots that are taught by students and enable the human learners thereby to develop a better understanding of the content ("teachable agent"-paradigm) (e.g., Biswas et al. 2005), or social robots that deliver the learning experience through social interaction with learners (robot tutors) (Köse et al. 2015). A recent review on social robotic tutors in education (Belpaeme et al. 2018) shows medium effect sizes for cognitive ($d = 0.70$) and affective ($d = 0.59$) outcomes when robots are compared to an ITS, an on-screen avatar, or human tutoring. There is also a recent approach that focuses on integrating ITS systems into physical robots to enhanced them with cognitive models of the learner, which has been referred to as Intelligent Tutoring Robots (ITR) (Yang / Zhang 2019). Besides these advancements, there are also concerns regarding the implementation of robots in classrooms, such as the fear that teachers will be replaced or the question whether robotic teaching assistants are in fact able to deal with the diversity of learners.

In our own research, we are particularly interested in adaptive artificial systems, with a focus on students' interindividual different emotions and motivation. Emotions are important prerequisites for complex learning processes and cognitive performance (Hagenauer / Hascher 2018; Rubach / Lazarides 2020). In learning and instruction, it is therefore necessary to react adaptively to students' emotions and motivation and to provide students with learning opportunities that enhance positive emotions such as enjoyment and curiosity (Lazarides / Buchholz 2019). To achieve this goal, the teacher needs to be able to perceive students' emotional states accurately and to promptly react to students' emotional and motivational needs. Addressing such challenges with AI in education is an important goal of our own research. In the next sections, we introduce our research projects that are designed to enable artificial intelligent teaching agents to assist teachers in tailoring instruction to students' individual emotional and motivational needs.

2. Our current research agenda: addressing learners' interindividually different characteristics with artificial agents

2.1 Research project "From understanding learners adaptive motivation and emotion to designing social learning companions"

Our research on artificial intelligence in education is located in the cluster of excellence 'Science of Intelligence' (https://www.scienceofintelligence.de/). The objective of our research projects in the cluster is to uncover the components and principles of *adaptive teaching behavior* in artificial and human teaching agents. Our research thereby brings together the expertise of different disciplines such as computer science, robotics, computer vision, educational psychology and educational research. In the following, we will briefly introduce the research projects and outline the expected insights into the role of artificial intelligence in educational research.

The research project "From understanding learners' adaptive motivation and emotion to designing social learning companions" aims to develop an approach for integrated game- and agent-based ITS and computational models that help to address the emotional needs of individual learners in heterogeneous groups of students. Thus, we aim to optimize scaffolding in social learning situations. On a more general level, we explore the principles that underlie adaptive teaching behaviors, including its components (e.g. prediction of the learner's emotional state). To reach this goal, we combine expertise from computer science, robotics, and educational research. Based on the learner and teacher models from the ITS, we develop a robotic learning companion that keeps an updated model of the learner and their current knowledge and motivational and emotional states, and acts accordingly (Lazarides et al. 2018). Thus, when selecting examples, tasks, materials or questions for each individual learner, the artificial agent will be adaptive to both the learner's level of cognitive performance and the learner's emotion and motivation. In a first step, we develop an adaptive ITS that includes a model of the learner's emotion, motivation, and performance and reacts adaptively to inter-individual differences and thus to each learner's individual learning preconditions. We build upon the established Betty's Brain ITS (Biswas et al. 2005) and investigate the emotional adaptivity of an adjusted ITS in learning situations. Using the ITS, we examine how novel user modelling approaches and feedback strategies can inform adaptive teaching that is guided by each individual learner's emotion, motivation, and performance. To empirically investigate the effects that our adaptive intelligent teaching system might have on learners' performance, we carry out psychological experiments using a pre- and post-test research design involving trait measures of epistemic emotions, learning strategies, value of learning, and self-efficacy of students, as well as state measures of epistemic emotions (Pekrun et al. 2017). In our research project, we hypothesize that an adaptive intelligent system that is capable of adapting hints for tasks to both the performance and emotional states of learners will lead to a more effective knowledge transfer – that is, increase task engagement and epistemic emotions such as enjoyment – than an adaptive intelligent teaching assistant that is purely performance-based. Our research will provide insights into the kind of information that emotions convey for the teaching and learning process, as well as underlying principles of adaptive teaching in regard to students' emotions. In educational research, we will increase knowledge about the role that motivation and emotion might play in the diagnostic process of a teacher and for the development of effective scaffolding strategies (Meyer / Turner 2007). Regarding artificial intelligence in education, we would expect that our artificially intelligent adaptive teaching assistants might, on a practical level, assist teachers in providing each individual learner with the level of cognitive support needed based on the learner's individual level of epistemic emotions and performance.

2.2 Research project "Social responsiveness and learning in heterogeneous groups: effects on human-human and human-robot interaction"

In the research project "Social responsiveness and learning in heterogeneous groups: Effects on human-human and human-robot interaction", we examine the concept of teacher sensitivity – conceptualized here as the social responsiveness of the teacher – and its role in knowledge transfer between humans, humans and artificial intelligent systems, and artificial agents. In learning interactions between humans, social responsiveness is particularly important to address the heterogeneity of learning groups (Rosenfeld / Rosenfeld 2004). In educational research, sensitive and responsive teaching behavior can be understood as a teacher's ability to accurately read a learner's signals and appropriately react to them (Pianta 1999). In human-robot interaction, it is well known that human companion robots need to be responsive to the emotions of learners to better interact with them (Churamani et al. 2017). In our research project, we build on research on Human-Robot Interaction and research in the field of educational psychology that focuses on teacher sensitivity and performance and aim to develop an artificial teaching assistant that is able to perceive social cues of individual learners, simulate and model socially responsive teaching behaviors, and use these abilities to adaptively communicate with individual learners. The robotic teaching assistant will be capable of socially responsive behaviors, including facial expressions and dialogue structures (Lazarides / Hellwich, 2020). On a general level, we address research questions that are relevant for educational psychology and computer vision. In educational psychology, we are interested in unknown facets of social responsive behaviors in learning-related interactions (e.g., concrete non-verbal cues of the teacher, such as turning to face the students and making eye contact when they ask a question). In computer vision, researchers are interested in whether knowledge transfer between artificial intelligent agents benefits from modelling emotions explicitly in parallel to the common processing steps in decision making. Research on human-robot interaction shows that responsiveness increases overall acceptance of artificial systems by human interaction partners - a central precondition for knowledge transfer (Cavedon et al. 2015). However, the role of robots that perceive and react to human behavior in learning situations are often not considered. Personalized Human-Robot Interactions require a high level of perceptual capabilities (i.e., recognizing a learner's activity). The main goal of this project, therefore, is to develop artificial systems with high-level perceptual capabilities in social learning situations that are able to simulate socially responsive behaviors. Our research will extend current knowledge about the behavioral components of socially responsive teaching behaviors in heterogeneous groups and contributes to research that is concerned with artificial intelligence in education by identifying the merits and constraints of socially responsive artificial teaching assistants for knowledge transfer in learning situations. We will be able to investigate the question of which perceptual capabilities a socially responsive artificial agent needs to effectively address individual needs of learners, for example by (i) identifying when a learner is confused, and by (ii) providing a timely and adaptive teaching response (e.g., providing easier examples) to the current state of the learner. In the next sections, we briefly introduce the empirical work on which our own research is based. This research concerns both non-intelligent and intelligent artificial agents and their role in educational processes.

3. Empirical studies on non-intelligent and intelligent systems in education

3.1 The perception of artificial agents and its impact on learning

Empirical research proposes that students' learning processes might be affected by their attitudes and perceptions of social robots (Reich-Stiebert / Eyssel 2015). Considering that reasoning skills are fundamental for learning, a recent study by our group (Spatola / Chevalère / Lazarides 2021) investigated the influence of the source of information on reasoning and motivation. More precisely, the authors investigated whether a given cue helping participants to succeed on a reasoning task (the Raven matrices), presented as coming from either a human or an artificial agent, could affect reasoning performance and achievement goals differently. Whenever participants first submitted an incorrect solution to a task, they received a cue and attempted the task a second time. For one group, the cue was presented as having come from a human agent, whereas for another group, the cue was presented as having been generated by an artificial agent. In the "perceived human teacher condition", participants showed higher performance accuracy during the subsequent attempt relative to when the same information was perceived as coming from an artificial agent. The findings were most apparent under a difficult condition than an easy condition. One possible interpretation of these results is that the cognitive load limits the amount of resources available for processing additional information – such as the source of information. In other words, the source of information seems to receive increased stereotypical representativeness ("trust people, not technology", Friedman et al. 2000) under high cognitive load, making the aid provided by the artificial agent appear less trustworthy and less likely to be used to improve performance. In a second experiment, the authors also assessed the impact of the source of information on achievement goals (Elliot et al. 2011). Results showed that motivational mechanisms mediated the effect of the perception of the information source on reasoning performance. When the source was thought of as artificial (vs. human), participants declared more self-oriented achievement goals (striving to improve their task performance in reference to their prior task performance) and less other-goal orientation (striving to outperform others). The non-social component, however, namely task-goal orientation (striving to understand the task), was invoked equally across conditions. A mediation model showed that participants in the "perceived artificial agent" condition experienced a decrease in other-goal orientation that mediated the negative pathway from the artificial agent condition to reasoning task performance.

3.2 Benefits of artificial teaching assistance on learning

Research has not only focused on the challenges, but also on the objective benefits of applying artificial agents to education. A recent study by Chevalère et al. (2021a) investigated the effectiveness of computer-assisted instruction (CAI) in Sciences and Technology on three topics related to Physics and Chemistry, Earth and Life Sciences, and Technology. The authors compared CAI to Inquiry-Based Learning (IBL) (Lazonder / Harmsen 2016).

The objects of knowledge were identical in the two conditions and were taken from a National Educational program. The CAI used in the study implied human-computer interactions where students could learn on their own and at their own pace using presented virtual material, including a diversity of training methods such as simulations, tutorials, and games. The procedure in the IBL condition involved hands-on work implying face-to-face interactions and collaboration with other classmates. The experiment was conducted on 509 students in middle school. In addition, the authors considered academic and socio-cognitive factors known to predict learning but rarely investigated in research into CAI and IBL (e.g., preknowledge, socioeconomic status, working memory capacity, and academic self-concept). Results showed that CAI was more efficient than IBL in Sciences and Technology, an advantage that was stable across individual differences in preknowledge, socioeconomic status, and academic self-concept. The benefits of CAI over IBL were more pronounced for students with higher working memory capacity (WMC) relative to their counterparts with lower WMC. Suggesting that learning with new technologies may depend on individual cognitive characteristics, higher benefits in students with higher WMC might result from the complex navigational constraints or the diversity of functionalities in CAI. While these findings call for caution and adjustments in the conditions required for learning with new technologies, they nevertheless highlight the fact that CAI is well-suited for learning topics in Science and Technology.

In another study, the authors investigated the effectiveness of CAI on a diverse range of topics from the National Educational Programme relative to the traditional "teacher-led" instructional method (Chevalère et al. 2021b). Focusing specifically on the influence of socioeconomic status on learning, the authors examined the effects of CAI in a large sample of middle and high school students (N = 806) from extreme socioeconomic backgrounds (disadvantaged students vs. highly privileged students, equally distributed). Results showed that CAI was more efficient than the traditional instructional method for learning a diverse range of content (Physics and Chemistry, Earth and Life Sciences, History and Geography, and Technology), but that students from disadvantaged backgrounds underperformed their highly privileged counterparts. Ensuring group equality (on sample size, gender ratio, and age) in a sub-sample of approximately half the total sample, students from disadvantaged backgrounds receiving CAI were compared to those from highly privileged backgrounds receiving traditional instruction. Results showed that the positive effects of CAI and the negative effects of socioeconomic status compensated each other. These promising results showed that CAI might be a useful method to cope with the detrimental consequences of social inequality in school.

3.3 Insights from studies using intelligent systems

Apart from improving the status of non-intelligent, yet adaptive technologies, research has also made considerable progress in developing systems endowed with artificial intelligence, such as ITS. In the past two decades, there have been substantial improvements in research on ITS. Among them are two notable forms of progress, one integrating the importance of social and emotional characteristics of human learning and the other bringing increased ITS sophistication through machine learning techniques.

3.3.1 Advances in psychological considerations integrated in ITS

ITS approaches that foster social learning have focused on the development of human-computer interactions. As an example, the ITS "Betty's Brain" (Biswas et al. 2005) was created based on the learning-by-teaching paradigm and involving more than one computer-based agent interacting with students. Inspired by research on effective human-human interactions in learning, Betty's Brain features two artificial agents: one mentor agent, whose role is to guide and supervise the learner while reading the content knowledge book; and one pupil agent, which learners will be instructing and monitoring by completing a causal map containing concepts that should be organized by causal relations. The efficiency of Betty's Brain was examined in a pre-post-test design pioneer experiment conducted in a sample of fifth-grade students who worked during six sessions of 45 minutes each, over a period of three weeks on the topic of ecosystem balance. Seven weeks after the initial experiment, students took two additional tests, one requiring recalling their causal map and a second test preparing them for future learning transfer, where they had to construct a causal map and answer questions related to a new but accessible topic. The authors manipulated three versions of Betty's Brain. The ITS version involved no teaching at all, while in the LBT and SRL variants, students could query and quiz Betty. In the SRL variant, Betty and Mr. Davis were more responsive and cued students on how to make use of self-regulation strategies. The results showed that the three groups improved from pre- to post-test and globally showed equal performance levels on the post-test and the delayed memory task. In contrast, students in the SRL variant best succeeded on the transfer task by showing higher performance levels in learning the new material, thus highlighting the crucial role of self-regulation strategies implemented in human-computer interactions.

Emphasizing the importance of emotional states in learning as evidenced in the field of educational psychology (Pekrun 1992), Graesser and colleagues built upon the famous ITS Auto-Tutor (Graesser et al. 1999) to consider learners' emotional characteristics in support of learning, by providing motivating feedback. More precisely, learners' emotional states were determined using a multimodal affect-detection algorithm integrating conversational cues, facial expressions, and posture sensors. Following student's responses, the novel "Affective AutoTutor" helped students regulate their emotional states when they arose. Based on student's performance, Affective AutoTutor delivered five levels of feedback articulating textual content using predetermined and randomly generated sentences, such as (positive) "Well done" or (negative) "That is not right" depending on students' response accuracy. This feedback was accompanied by modulations of the facial emotions expressed by the tutor agent to indicate approval, disappointment, scepticism, and empathy, along with emotional modulations of speech. Based on the emotion-detection algorithm, Affective AutoTutor also generated motivational feedback aimed at influencing students' affective states. Two variants of the ITS were compared, implementing distinct motivational strategies (D'Mello / Graesser 2013). The first version was "Supportive" and delivered empathetic and motivational support to students and attributed the source of their failure to the materials of the task or to itself. The other version, "Shake-up" was playfully rude and attributed the source of emotion to students, while still encouraging them. In two experiments, the two variants were compared to the Regular AutoTutor, not adaptive to emotional states. Results showed that the supportive variant consistently outperformed the shakeup variant. A detailed examination revealed that the benefits of the supportive variant over the regular tutor depended on the student's level of mastery, with benefits only apparent for students with low domain knowledge. A follow-up study found that time modulated the interaction between knowledge level and ITS variant. In the first training session, the regular tutor benefited students with high domain knowledge, while in a subsequent session the supportive variant benefitted students with lower domain knowledge.

3.3.2 Advances in ITS using machine learning and mathematical frameworks

Apart from advances in psychological considerations, the sophistication of ITS from a computer-science perspective has made significant progress as well. For students to learn a given content, the latter typically requires explicit formalization in the domain model, with well-defined and structured representations of knowledge objects (i. e., an expert model). As part of the techniques used to accompany students through the learning process, ITS usually provides feedback based on student's actions, whose correctness is determined through comparisons to the expert model. Although this approach has led to success for ITS in a range of topics, these are limited to well-defined objects of knowledge, whose construction requires substantial work, and which does not address ill-defined problems such as the ones assessed subjectively (e.g., usefulness; Le et al. 2013). Novel ITS approaches have made their mark in addressing these issues, with notable methodological advances. In the absence of an exact expert model, the main principle of these advances is to compare students' actions to other students' solution attempts, or example solutions created by experts for similar problems using machine learning algorithms. A study by Gross et al. (2015), for example, used modelling techniques representing data in the form of typical examples based on the comparison between given data and the learned prototype. Based on pairwise proximities to students' answers, a pedagogical module provided feedback that explicitly asked students to compare their answer to similar, yet not identical elements derived from a solution space. This promotes students' metacognitive thinking by asking them to explain possible differences between their answers and those derived from a solution space, searching for mistakes, and thinking about how to fix them. The suitability of this novel ITS approach (providing sample solutions) was examined in several pilot studies revealing promising results: Learners and experts positively rated the method and judged it as helpful in a majority of cases. Despite much effort is devoted to their development, ITS are however still limited, especially concerning their lack of widespread integration of reinforcement learning techniques to provide sophisticated and comprehensive student models and in predicting long-term academic outcomes such as school dropout or course failure (Baker 2016).

4. Challenges and conclusions

When reviewing research on the role of AI in education, and particularly in school education, it is important to also discuss the challenges of implementing intelligent technology in classrooms. Theoretical and related methodological challenges of using AI in education is that we know little about how the interaction between humans – and in our case human learners – and machines affect cognitive as well as motivational processes. Our own research has pointed out that learners perform differently and pursue different goal orientations in achievement situations when they are convinced that hints and information come from artificial systems rather than from humans (Spatola / Chevalère / Lazarides 2021). However, we need to extend knowledge on how social interactions with artificial systems in learning situations affect learners' socio-emotional, motivational and cognitive processes – also considering the role of age, gender, ethnical and language background for these interactions. Furthermore, there are many more practical challenges. Ballod and Klein (2020), for example, outlined that data protection was among the most frequently stated perceived risks of an implementation of AI in school-related learning settings in their non-representative survey. This concern seems understandable because, for example, ITS requires a large amount of data and it is important to provide information about the further processing of this data, as well as data usage purposes and data protection regulations (Meier 2020). In Germany, as in other countries of the European Union (EU), the “EU General Data Protection Regulation” (“EU Datenschutzgrundverordnung”; DSGVO) and its specific data protection acts at the level of the sixteen federal states of Germany, as well as the school laws of the federal states, set guidelines and regulations that need to be considered when implementing intelligent artificial teaching assistants in schools.

Another topic is the concern that has been described in public discourse that artificial agents might “replace” teachers, which is unlikely and undesirable as interactions between teachers and students are complex relationships shaped by a learning culture that goes beyond principles of learning and instruction (Lazarides / Schiefele 2021). However, as our literature review and our own research projects emphasizes, adaptive systems and social robots can support teachers when dealing with highly diverse groups of students by improving the effectiveness of instruction, without substituting the teacher (Mohammed / Watson 2019).

Acknowledgement

This research is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany’s Excellence Strategy – EXC 2002/1 “Science of Intelligence” – project number 390523135.

Literature

Baker, Ryan. S. (2016): Stupid tutoring systems, intelligent humans. In: International Journal of Artificial Intelligence in Education, 26 (2), 600–614.

Ballod, Matthias / Klein, Stefanie (2020): KI in der Bildung. Erste Befundlage zur Online-Befragung. Information. In: Wissenschaft & Praxis, 71 (1), 3–4.

Belpaeme, Tony / Kennedy, James / Ramachandran, Aditi / Scassellati, Brian / Tanaka, Fumihide (2018): Social robots for education: A review. In: Science Robotics, 3 (21), 1–18. https://doi.org/10.1126/scirobotics.aat5954.

Beese, Elizabeth Brott (2019): A process perspective on research and design issues in educational personalization. In: Theory and Research in Education, 17(3), 253–279. https://doi.org/10.1177/1477878519893963

Biswas, Gautam / Leelawong, Krittaya / Schwartz, Daniel / Vye, Nancy (2005): Learning by teaching: A new agent paradigm for educational software. In: Applied Artificial Intelligence, 19 (3–4), 363–392.

Cavedon, Lawrence / Kroos, Christian / Herath, Damith / Burnham, Denis / Bishop, Laura / Leung, Yvonne / Stevens, Catherine J. (2015): "C′ Mon dude!": Users adapt their behaviour to a robotic agent with an attention model. In: International Journal of Human-Computer Studies, 80, 14–23. https://doi.org/https://doi.org/10.1016/j.ijhcs.2015.02.012.

Chevalère, Johann / Cazenave, Loreleï / Berthon, Mickaël / Martinez, Ruben / Mazenod, Vincent / Borion, Marie-Claude / Pailler, Delphine / Rocher, Nicolas / Cadet, Rémi / Lenne, Catherine / Maïonchi-Pino, Norbert / Huguet, Pascal (2021a): Inquiry-Based Learning versus Computer-Assisted Instruction. Manuscript submitted for publication.

Chevalère, Johann / Cazenave, Loreleï / Berthon, Mickaël / Martinez, Ruben / Mazenod, Vincent / Borion, Marie-Claude / Pailler, Delphine / Rocher, Nicolas / Cadet, Rémi / Lenne, Catherine / Maïonchi-Pino, Norbert / Huguet, Pascal (2021b): Compensating the socioeconomic achievement gap with computer-assisted instruction. Manuscript submitted for publication.

Churamani, Nikhil / Kerzel, Matthias / Strahl, Erik / Barros, Pablo / Wermter, Stefan (2017): Teaching emotion expressions to a human companion robot using deep neural architectures. In: IEEE (Ed.): International Joint Conference on Neural Networks (IJCNN), Anchorage, 627–634.

Connor, Carol McDonald (2019): Using technology and assessment to personalize instruction: Preventing reading problems. In: Prevention Science, 20 (1), 89–99.

Dumont, Hanna (2019): Neuer Schlauch für alten Wein? Eine konzeptuelle Betrachtung von individueller Förderung im Unterricht. In: Zeitschrift für, 22 (2), 249–277.

Elliot, Andrew J. / Murayama, Kou / Pekrun, Reinhard (2011): A 3×2 achievement goal model. In: Journal of Educational Psychology, 103 (3), 632–648.

Friedman, Batya / Khan, Peter H. / Howe, Daniel C. (2000): Trust online. In: Communications of the ACM, 43 (12), 34–40.

Graesser, Arthur C. / Wiemer-Hastings, Katja / Wiemer-Hastings, Peter / Kreuz, Rogen / Tutoring Research Group, University of Memphis (1999): AutoTutor: A simulation of a human tutor. In: Cognitive Systems Research, 1 (1), 35–51.

Gross, Sebastian / Mokbel, Bassam / Hammer, Barbara / Pinkwart, Niels (2015): Learning feedback in intelligent tutoring systems. In: KI-Künstliche Intelligenz, 29 (4), 413–418.

Hachfeld, Axinja / Lazarides, Rebecca (2020): The relation between teacher self-reported individualization and student-perceived teaching quality in linguistically heterogeneous classes: An exploratory study. In: European Journal of Psychology of Education. https://doi.org/https://doi.org/10.1007/s10212-020-00501-5.

Hagenauer, Gerda / Hascher, Tina (Hrsg.) (2018): Emotionen und Emotionsregulation in Schule und Hochschule. Münster, New York.

Köse, Hatice / Uluer, Pınar / Akalın, Neziha / Yorgancı, Rabia / Özkul, Ahmet / Ince, Gökhan (2015): The effect of embodiment in sign language tutoring with assistive humanoid robots. In: International Journal of Social Robot, 7 (4), 537–548.

Kulik, James A. / Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: a meta-analytic review. In: Review of Educational Research, 86 (1), 42–78.

Lazarides, Rebecca / Buchholz, Janine (2019): Student-perceived teaching quality: How is it related to different achievement emotions in mathematics classrooms?

In: Learning and Instruction, 61, 45–59. https://doi.org/10.1016/j.learninstruc.2019.01.001.
Lazarides, Rebecca / Hafner, Verena / Pinkwart, Niels (2018): From understanding learners' adaptive motivation and emotion to designing social learning companions. Unpublished research report. University of Potsdam, HU Berlin.
Lazarides, Rebecca / Hellwich, Olaf (20C20): Social responsiveness and learning in heterogeneous groups: Effects on human-human and human-robot interaction. Unpublished research report. University of Potsdam, TU Berlin.
Lazarides, Rebecca / Schiefele, Ulrich (2021): Von der Lehrermotivation zur Schülermotivation. Theoretische Perspektiven und empirische Befunde zur Förderung von Lernmotivation im Unterricht. In: Lazarides, R. / Raufelder, D. (Hrsg.): Motivationsförderung in unterrichtlichen Lehr-Lernkontexten. (Edition ZfE, Bd. 10). Wiesbaden, 3–28.
Lazonder, Ard W. / Harmsen, Ruth (2016): Meta-analysis of inquiry-based learning: Effects of guidance. In: Review of Educational Research, 86 (3), 681–718.
Le, Nguyen-Thinh / Loll, Frank / Pinkwart, Niels (2013): Operationalizing the continuum between well-defined and ill-defined problems for educational technology. In: IEEE Transactions on Learning Technologies, 6 (3), 258–270.
Ma, Wenting / Adesope, Olusola O. / Nesbit, John C. / Liu, Qing (2014): Intelligent tutoring systems and learning outcomes: A meta-analysis. In: Journal of Educational Psychology, 106 (4), 901–918. https://doi.org/http://dx.doi.org/10.1037/a0037123.
McCombs, Barbara L. (2010): Learner-centered practices: Providing the context for positive learner development, motivation, and achievement. In: Meece, Judith L. / Eccles, Jacquelynne S. (Hrsg.): Handbook of research on schools, schooling and human development. New York, Oxon, 78–92.
Meier, Christoph (2020): Adaptive Lernumgebungen. Heterogenität und das Bedürfnis nach Personalisierung. In: eLearning Journal, 2020 (3), 44–47.
Meyer, Debra K. / Turner, Julianne C. (2007): Scaffolding emotions in classrooms. In: Schulz, Paul A. / Pekrun, Reinhard (Hrsg.): Emotion in Education. Amsterdam, 243–258.
Mohammed, Phaedra S. / Watson, Eleanor 'Nell' (2019): Towards inclusive education in the age of artificial intelligence: Perspectives, challenges, and opportunities. In: Knox, Jeremy / Wang, Yuchen / Gallagher, Michael (Hrsg.): Artificial intelligence and inclusive education. Singapore, 17–37.
Ocumpaugh, Jaclyn / Baker, Ryan S. / Rodrigo, Ma. / Mercedes T. (2015): Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP) 2.0 Technical and Training Manual. Technical Report.
Pekrun, Reinhard (1992): The impact of emotions on learning and achievement: Towards a theory of cognitive/motivational mediators. In: Applied Psychology, 41 (4), 359–376.
Pekrun, Reinhard / Vogl, Elisabeth / Muis, Krista R. / Sinatra, Gale M. (2017): Measuring emotions during epistemic activities: The Epistemically-Related Emotion Scales. In: Cognition and Emotion, 31 (6), 1268–1276.
Pianta, Robert C. (1999): Enhancing relationships between children and teachers. Between Children and Teachers. Washington D. C. https://doi.org/ http://dx.doi.org/10.1037/10314–000.

Reich-Stiebert, Natalia / Eyssel, Friederike (2015): Learning with educational companion robots? Toward attitudes on education robots, predictors of attitudes, and application potentials for education robots. In: International Journal of Social Robotics, 7 (5), 875–888.
Rosenfeld, Melodie / Rosenfeld, Sherman (2004): Developing teacher sensitivity to individual learning differences. In: Educational Psychology, 24 (4), 465–486. https://doi.org/https://doi.org/10.1080/0144341042000228852.
Ross, Manus / Graves, Corey A. / Campbell, John W. / Kim, Jung H. (2013): Using support vector machines to classify student attentiveness for the development of personalized learning systems. 12th International Conference on Machine Learning and Applications.
Rubach, Charlott / Lazarides, Rebecca (2019): Die Rolle der Individualisierung im Mathematikunterricht für die Motivation von Lernenden am Ende der Sekundarstufe I. In: Knauder, Hannelore / Reisinger, Christa-Monika (Hrsg.): Individuelle Förderung im Unterricht: Empirische Befunde und Hinweise für die Praxis. Münster, New York, 115–130.
Rubach, Charlott / Lazarides, Rebecca (Hrsg.) (2020): Emotionen in Schule und Unterricht. Leverkusen-Opladen.
Spatola, Nicolas / Chevalère, Johann / Lazarides, Rebecca (2021): Human vs computer: Which effect does the source of information have on information processing, cognitive performances and achievement goal orientations? In: Paladyn, Journal of Behavioral Robotics, 12 (1), 175–186. https://doi.org/10.1515/pjbr-2021–0012.
van de Pol, Janneke / Volman, Monique / Beishuizen, Jos (2010): Scaffolding in teacher–student interaction: A decade of research. In: Educational Psychology Review, 22 (3), 271–296. https://doi.org/https://doi.org/10.1007/s10648–010–9127–6.
van der Vorst, Tommy / Jelicic, Nick (2019): Artificial Intelligence in Education: Can AI bring the full potential of personalized learning to education? In: 30th European Conference of the International Telecommunications Society (ITS): ”Towards a Connected and Automated Society”. Helsinki.
Vygotsky, Lev Semyonovich (1978): Mind in society-The development of higher psychological processes. Cambridge.
Walkington, Candace / Bernacki, Matthew (2020): Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. In: Journal of Research on Technology in Education, 52 (3), 235–252. https://doi.org/https://doi.org/10.1080/15391523.2020.1747757.
Yang, Jinyu / Zhang, Bo (2019): Artificial intelligence in intelligent tutoring Robots: A systematic review and design guidelines. In: Applied Sciences, 9 (10), 2078.

Short biographies

Rebecca Lazarides, Professor for School and Instructional Research. Research fields: learning and instruction; motivation and emotion; interindividual motivational differences; teacher professional competence; adaptive AI in education.
Anschrift: Department of Education, Faculty of Humanities, University of Potsdam, Karl-Liebknecht Str 24–25, 14476 Potsdam OT Golm / *E-Mail:* rebecca.lazarides@uni-potsdam.de

Johann Chevalère a postdoctoral researcher in psychology with a focus on students' emotional processing and higher mental functions. Research fields: cognitive psychology; educational psychology; adaptive AI in education.
Anschrift: Department of Education, Faculty of Humanities, University of Potsdam, Karl-Liebknecht Str 24–25, 14476 Potsdam OT Golm / *E-Mail:* chevalere@uni-potsdam.de