xIlkogretim Online - Elementary Education Online,2021; Vol 20 (Issue 5): pp.3205-3211
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2021.05.348

Supporting Self-Regulated Learning by Affect Detection and Responding in AI-driven Learning Systems

Faisal Rehman Channa, Faculty of Education, University of Oulu, Finland
Dr Pir Suhail Ahmed Sarhandi, Department of Linguistics and Human Sciences, Begum Nusrat Bhutto Women University, Sukkur, Pakistan**,** suhail.sarhandi@bnbwu.edu.pk
Firdous Bugti, Department of Education, Shah Abdul Latif University, Khairpur, Pakistan
Dr Imtiaz Ali Brohi, Begum Nusrat Bhutto Women University, Sukkur, Pakistan

Abstract- Emotions play a vital role in self-regulated learning (SRL)processes and drastically influence cognitive functioning.Along with creating individualized, engaging, flexible and inclusive learning environments, Artificial intelligence (AI) learning systems, especially intelligent tutoring systems (ITSs) have the potential to sense affective states of a learner and respond to them to maintain learning flow. This paper discusses the concept of AI in education (AIEd) followed by the explanation of the role of emotions in SRL. Highlighting theoretical and technical aspects, it provides a discussion of ITS with an example of its benefits in learning.It also overviews affect detection and responding in affect-sensitive ITSs. Before concluding, the paper highlights some limitations of the AI learning systems to detectaffective states and achieve maximum student learning outcomes.

Keywords: Emotions in Self-regulated Learning, Affective States, Affect Detection, Artificial Intelligencein Education, Intelligent Tutoring Systems.

I. INTRODUCTION

Emotions can influence cognitive behaviors such as attention focusing, decision making, reasoning, and memory recalling(Forgas, Wyland, & Laham, 2006).They are influential factors in learning and achievement.For an in-depth understanding of the influence of emotions on student learning outcomes, many researchers have been focusing on creating learning environments which sense and respond to students'emotions (affects), i.e. boredom, confusion, frustration, anxiety(Afzal & Robinson, 2011;D'Mello & Graesser, 2010;Woolf et al., 2010;Conati & Maclaren, 2009;Chaffar, Derbali, & Frasson, 2009;Forbes-Riley, Rotaru, & Litman, 2008). Technological advancement, especially the adaptation and harnessing the power of AIEd can be a transformative factor for not only understanding learning patterns but also supporting SRL by detection and responding students' affective states during learning with AI systems.Unlike one-size-fits-all teaching practices, the AI learning systems can influence affective states to foster deep thoughtfulness and model-based reasoning, e.g. analyzing causal relationships, critical thinking, problem-solving, and bridging inferences (D'Mello & Graesser, 2012).ITS, powered by AI technology, has been beneficial in not only detecting affects and influencing them for maximum learning but also helping learners regulate their learning(Ma, 2014;D'Mello & Graesser, 2012;D'Mello et al., 2008;Long & Aleven, 2013).

The paperbriefly explores the concept of AIEd and overviews the role of emotions in SRL. It also elaborates the most common AI learning system, ITSbydiscussingtheoretical and technical perspectives of it. Besides, it explains Bettys' Brain as an example of ITS for supporting SRL. It also highlights affect sensitive AI learning system. Lastly, the paper also discusses some limitations of ITSs beforethe conclusion.

Concept of AI in Education

Defining AI is quite challenging even for experts in the field (Luckin et al., 2016). However, AI can be defined asa tool that has been designed and developed to assist in or replace decision-making processes through analysis of data, and prediction of the best value for a designated outcome variable, which is conveyed through a user interface(Josep Seering, 2018). AIEd specifically AI systems for learning can be proposed as technological tools programmed to interact decision-making intelligent actions and predictions through intelligence capabilities of computational systems generated after a deep systematic analysis of digital data gathered from various digital tools (i.e. visual perception, facial recognition) (Russell, 2016; ODE, 2005).

AIEd augments teachers' intelligence by providing them with sets of predictions and recommendations to maximize learning (personality growth, development in the sense of self-efficacy and self-esteem)(Underwood & Luckin, 2011). AIEd pivots around models which are designed by traits of students, teachers, affective, metacognitive, collaborative factors of learning, the learning environment and the context of learners (Luckin, 2010). After going through systematic analysis of various digital data (i.e. administrative, demographic, students'interactions with technology, peer interactions, students' affect), gathered from physiological sensors and sophisticated digital tools (D'Mello, Picard, & Graesser, 2007; Arroyo, 2009), AIEd can enable teachers to see the best calculations, recommendations and predictions about better student learning outcomes which otherwise are hard for human intelligence to judge.

The Role of Emotions in Self-Regulated Learning

Self-regulated learning is a self-guided process of learning in which a learner deliberately organizes his/her metacognition, motivation and active behavioral engagement to attain learning goals(Zimmerman, 1986).SRL researchers(Efklides, 2011;Pintrich, 2000;Zimmerman, 2000) have regarded affect as a vital feature of SRL. In an academic setting, emotions are defined as sets of psychological processes, including affective, motivational, cognitive, physiological and expressive elements(Shuman & Scherer, 2014). Emotions of learners before, during and after their learning task can impact their self-regulatory processes.The relationship between affect and learning has been studied, where emotions such as delight, boredom, confusion, frustration are key factors(Barrett, 2009;Russell, 2003).

Unresolved confusion during learning can lead to annoyance, irritation, frustration, and anger. Contrary, a learner may feel a range of positive emotions when he/she tackles misunderstandings. Studies have shown that both lectured classroom instructions and advanced technology-enhanced learning environments can stimulate a range of emotions(D'Mello, 2013;Pekrun, Goetz, Titz, & Perry, 2002), consequently, influence SRL.For instance, learners'skills to regulate their emotions are linked to how well they proceed in a learning task(Pekrun, 1992).Positive emotions can help learners design goals, encourage engagement in learning task, promote creative problem solving, and support self-regulation(Clore & Huntsinger, 2009). Whereas, stimulation of negative emotions about taking exams and studying hinder academic progress, irregulate SRL, engender school dropouts and badly impact health(Zeidner, 2014).

AI Learning Systems:

AI learning systems have the potential to drive prediction of learners' cognition, emotion, self-efficacy, and learning thinking (Woolf, 2013). Intelligent computational technologies, like human tutors' interactions with students, reveal students' learning patterns, self-interest, potential, and weaknesses (Arroyo, 2009).AI-poweredITS isone of the common learning systems of AIEd. It offers step-by-step tutorials, tailored for each learner in well-coherent subjects such as physics and mathematics(Alkhatlan & Kalita, 2018).Most of ITSs are programmed on the following four models(Holmes, Bialik, & Fadel, 2019);

a) **The Domain Model:** It represents knowledge about the topic that the ITS intents to help the learners learn. For example, topic knowledge can be mathematical equations, circulatory system etc.

b) **The Pedagogy Model:** It showsknowledge about pedagogical approaches, drawn from teaching experts and research findings in the learning sciences. Many ITSs have been programmed with pedagogical knowledge of instructional approaches, cognitive load, interleaved practice, the zone of proximal development, and formative feedback.

c) **The Learner Model:** Itrepresents knowledge about learners' interactions with ITS, content that has challenged the learners, their misunderstandings and affective states while working on the system. The model augments stored knowledge of each learner with knowledge of all learners who have interacted with the system. The machine learning technique develops the model's knowledge to predict suitable pedagogical methods and domain knowledge for any specific learner at any particular stage of his/her learning.

d) **The Open Learner Model:** It aims to make the learning of students and the decision taken by the system visible for both teachers and students. It informs teachers about each learner's learning (patterns, approach, and any misconception) and enables learners to see their learning attainment and challenges the faced during learning.

Drawing on these models, ITSs optimize learning environment by presenting personalized, engaging, and flexible learning activities. Program designing and sophisticated technology of the systemsenable them to detect learners' affective states tounderstand them at a specific learning area of study and maximize learning outcomes. According to the learning attitude of learners, ITSs not only guide and provide particular feedback but also trigger learning interests (D'Mello et al., 2008) through the self-explanation, self-regulation and self-assessment. ITSs are programmed for subject-specific areas such as mathematics, medicine, and reading to assist learners in gaining subject-specific, cognitive and metacognitive knowledge (Ma, 2014). Besides, to sustain learning engagement and helpin the self-regulatory learning process, ITSs can recommend the most suitable level of learning activities according tothe learning context, content and understanding of the learners (Azevedo and Hadwin, 2005; VanLehn, 2006).

From a theoretical perspective, ITSs are programmed according to explanation-oriented constructivist theories of learning(Aleven & Koedinger, 2002;Bransford, Goldman, & Vye, 1991;Piaget & Cook, 1952;Vygotsky, 1980). Theapproach establishes that learners need to build structured and explanation-basedmeaning and knowledge by interacting with the learning environment and individuals. Simply, telling and doing enable learners to learn. Instead of providing mere information, learning environments should trigger active construction of knowledge and steer learners toward attainment of learning outcomes by giving them feedback and explanations on their construction of knowledge. ITSs are based on such constructivist principles, as they provide a learning environment which simulates dialogue moves to offerexplanation and feedback to learners for constructing knowledge and solving problems(D'Mello, 2012).

Betty's Brain

Betty's Brain(Andres et al., 2019;Munshi, Rajendran, Ocumpaugh, Moore, & Biswas, 2018; Munshi et al., 2018) is an agent-based open-ended learning environment program, based on AI tools (ITS) that encourages knowledge construction and self-regulated learning by applying a learning-by-teaching approach to teach scientific knowledge in an engaging manner (Andres et al., 2019). The pedagogical approach of Betty's Brain not only improves a scientific understanding of students but also helps them enrich their cognitive and metacognitive skills (Munshi et al., 2018). Moreover, like a human tutor, Betty's Brain senses affective states of the learners and accordingly designs pedagogical strategies to assist maintain learning flow to maximize learning outcomes(Munshi et al., 2018). Through the character of Betty, students get learning resources of a specific scientific topic to read and build a causal map of their understanding of it. Unlike real-world teaching methodologies, with this AI virtual agent, students take charge of their learning by teaching Betty what they have understood from the learning resources, provided in the learning system. For the attainment of learning objectives, students needto make sure Betty does reflect their level of understanding. Responses of Betty to questions and taking quizzes, which are designed by another virtual mentor (an experienced teacher, Mr. Davis) reflect students' learning. Mr. Davis is in-charge of mentoring both, Betty's response as well as students' teaching practices to Betty and their learning.On achieving learning objectives, it admires students for teaching it well. Betty's feedback to students reveals different cognitive and affective behavior(Andres et al., 2019). The findings highlight the importance of scaffold to low performers students according to their cognitive and affective interactions in the learning setting to assist them in self-regulated learning (Munshi et al., 2018). In short, Betty's Brain enables learning with an open-ended learning environment, provides students with scaffolding and feedback to improve reading, planning, modeling and keep track of learning activities. (see https://wp0.vanderbilt.edu/oele/bettys-brain/)

Affect Detection in AI Learning System:

Affective AutoTutor is an AI-driven intelligent torturing system (ITS)thatsenses the affective states, i.e. boredom, flow/engagement, confusion, frustration) of a learner by regulating conversational cues, body postures, and facial features(D'Mello, 2012).Itmaintains motivational and pedagogical dialogues according to affective states of learners. With AI techniques and using sophisticated digital sensors, theAutotutor detects a learner's affect by analyzing body postures, facial signs, galvanic skin response, conversational clues, interactions logs and language (Calvo, 2010).According to cognitive, affective and motivational states of a learner, it integrates learning content and pedagogical strategies to keep learners engaged, uplift self-confidence and presumably regulates learning(Craig, Graesser, Sullins, & Gholson, 2004;D'Mello, Craig, Sullins, & Graesser, 2006). For instance, if the learner is experiencing negative emotions i.e. frustration and about to withdraw from the learning activity, the tutor senses his/her affective states and then accordingly generates cues to further the learner in building knowledge and creates emphatic dialogues to boost the confidence of the learner(Woolf et al., 2010). If the learner is getting bored, the tutor presents engaging content by incorporating pedagogical strategies to maintain the interest of the learner(D'Mello et al., 2008).

Throughout the learning process, it guides learners to construct knowledge, deliver specific instructions, making learning engaging and motivates for SRL. As per the typing of the learner, it provides feedback and drives him/her for further input. Besides, by giving hints, it urges the learner to fill missing information, identifies and rectifies misconceptions, responds to the learner's questions and summarizes the learning content(Graesser, Jackson, & McDaniel, 2007). Moreover, it communicates with a learner in a natural language like a real human tutor and applies engaging pedagogical tactics (Graesser, 2004; Graesser, 2008). A research study found that the learning gains in the topic of physics from affective Autotutor were almost equivalent to one-to-one human tutoring, having experience tutorship in a computer-mediated discussion (Vanlehn, 2007).With the advancement in AIEd, AutoTutor systems would have more advantages over human-tutors with advanced pedagogical approach(Graesser, 2016).

II. Limitations

AI learning tools, especially affect-sensitive AutoTutor, despite achieving significant efficiency in detection students' affective states and helping regulate their learning, have some limitations.First, according to a study(Andres et al., 2019), although theITS can sense an affective state of boredom as a feature of students' knowledge, it hardly analyzes that it is not an indication of knowledge construction. The same study also concluded that recognition of affective patterns by the ITS could be related to prior knowledge of the learners than to learning gains.Second, besides the annoying fractional percentage of learners, conversational dialogue feature in the ITS has been ineffective when a learner takes more time to proceed and has surface knowledge of the content(D'Mello, 2012).Thirdlimitation is about the loss of patience among learners when conversation breaks down between the ITS and the learners. The causes of such breakdown are incomplete curriculum script, imperfect student modeling, and misclassification of learner's speech. Fourth, from a technical perspective, the ITS still needs to be equipped with state-of-the-art affect sensitive sensors and signal processing algorithms powered by machine learning techniques to accurately sense the affective conditions of a learner within real-time constraints(D'Mello et al., 2008).Last, analyzing the learning outcomes of low and high performers, ITS (Betty's Brain)has yielded limited benefits(Munshi et al., 2018).A study concluded that detecting frustration, caused by delayed success, among high performing students, the ITS succeeded to influence their affect and engaged them in the learning activity(Munshi et al., 2018). Whereas, the same affective state led low performing students withdrew from the learning environment, indicating the ITS's limitation in maintaining engagement.

III. Conclusion

Emotions play a vital role in the learning process, as learners'affective states influence cognitive enterprises, motivation, self-regulation and learning achievement(Chew, Zain, & Hassan, 2013;Kim, Park, & Cozart, 2014;Mega, Ronconi, & De Beni, 2014;Tempelaar, Niculescu, Rienties, Gijselaers, & Giesbers, 2012). Since the emotions are key "drivers" for learning(Rienties & Rivers, 2014), their measuring and monitoring would be highly beneficial for maximum attainment of learning objectives and helping students regulate their learning.The paper attempted to review the concept of AIEd and explained the role of emotion in SRL. It highlighted technical and theoretical aspects of AI learning systems (ITSs) which detect and respond to students' affective states. Besides,it provided a discussion of AI learning systems thatcan elevate confidence about AIEd's promising role in transforming students'learning experiences with maximum learning outcomes.Regardless of different names, versions and applications, AI learning systems can tackle long-term challenges of learning by providing an opportunity of individualized, engaging and lifelong learning partner to each learner.Although there are some limitations of ITSs, with the progression in AI technologies to constantly measure and unpack emotions, it would be possible for AI-powered ITSs to regulate students' emotions effectively towards the attainment of maximum learning objectives.

References

1. Afzal, S., & Robinson, P. (2011). Natural affect data: Collection and annotation. In *New perspectives on affect and learning technologies* (pp. 55–70). Springer.
2. Aleven, V. A., & Koedinger, K. R. (2002). An effective metacognitive strategy: Learning by doing and explaining with a computer-based cognitive tutor. *Cognitive Science*, *26*(2), 147–179.
3. Alkhatlan, A., & Kalita, J. (2018). Intelligent Tutoring Systems: A Comprehensive Historical Survey with Recent Developments. *ArXiv Preprint ArXiv:1812.09628*.
4. Andres, J. M. A. L., Paquette, L., Ocumpaugh, J., Jiang, Y., Baker, R. S., Karumbaiah, S., … Biswas, G. (2019). Affect sequences and learning in Betty's brain. *ACM International Conference Proceeding Series*, 383–390. https://doi.org/10.1145/3303772.3303807
5. Arroyo, I. (2009). Emotion sensors go to school. *Frontiers in Artificial Intelligence and Applications*, *200*(1), 17–24. Retrieved fromhttp://www.scopus.com/scopus/openurl/link.url?ctx_ver=Z39.882004&ctx_enc=info:ofi/enc:UTF-8&svc_val_fmt=info:ofi/fmt:kev:mtx:sch_svc&svc.abstract=yes&rft_id=info:eid/2-s2.0-73149108640&rfr_dat=partnerID:45
6. Azevedo Rogerand Hadwin, A. F. (2005). Scaffolding Self-regulated Learning and Metacognition – Implications for the Design of Computer-based Scaffolds. *Instructional Science*, *33*(5), 367–379. https://doi.org/10.1007/s11251-005-1272-9
7. Barrett, L. F. (2009). Variety is the spice of life: A psychological construction approach to understanding variability in emotion. *Cognition and Emotion*, *23*(7), 1284–1306.
8. Bransford, J. D., Goldman, S. R., & Vye, N. J. (1991). Making a difference in people's ability to think: Reflections on a decade of work and some hopes for the future. *Influences on Children*, *147*, 180.
9. Calvo, R. A. (2010). Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. Retrieved from https://ieeexplore.ieee.org/document/5520655
10. Chaffar, S., Derbali, L., & Frasson, C. (2009). Inducing positive emotional state in Intelligent Tutoring Systems. *AIED*, *2009*(200), 716–718.
11. Chew, B. H., Zain, A. M., & Hassan, F. (2013). Emotional intelligence and academic performance in first and final year medical students: a cross-sectional study. *BMC Medical Education*, *13*(1), 44.
12. Clore, G. L., & Huntsinger, J. R. (2009). How the object of affect guides its impact. *Emotion Review*, *1*(1), 39–54.
13. Conati, C., & Maclaren, H. (2009). Empirically building and evaluating a probabilistic model of user affect. *User Modeling and User-Adapted Interaction*, *19*(3), 267–303.
14. Craig, S., Graesser, A., Sullins, J., & Gholson, B. (2004). Affect and learning: an exploratory look into the role of affect in learning with AutoTutor. *Journal of Educational Media*, *29*(3), 241–250.
15. D'Mello, S., Jackson, T., Craig, S., Morgan, B., Chipman, P., White, H., … Picard, R. (2008). AutoTutor detects and responds to learners affective and cognitive states. *Workshop on Emotional and Cognitive Issues at the International Conference on Intelligent Tutoring Systems*, 306–308.
16. D'Mello, S. K., Craig, S. D., Sullins, J., & Graesser, A. C. (2006). Predicting affective states expressed through an emote-aloud procedure from AutoTutor's mixed-initiative dialogue. *International Journal of Artificial Intelligence in Education*, *16*(1), 3–28.
17. D'mello, S. K., & Graesser, A. (2010). Multimodal semi-automated affect detection from conversational cues, gross body language, and facial features. *User Modeling and User-Adapted Interaction*, *20*(2), 147–187.
18. D'Mello, S, Picard, R. W., & Graesser, A. (2007). Toward an Affect-Sensitive AutoTutor. *IEEE Intelligent Systems*, *22*(4), 53–61. https://doi.org/10.1109/MIS.2007.79
19. D'Mello, Sidney. (2012). AutoTutor and affective autotutor: Learning by talking with cognitively and emotionally intelligent computers that talk back. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, *2*(4), 1–39. Retrieved from http://dl.acm.org/citation.cfm?id=2395128

20. D'Mello, Sidney. (2013). A selective meta-analysis on the relative incidence of discrete affective states during learning with technology. *Journal of Educational Psychology*, *105*(4), 1082.
21. DMello, S., & Graesser, A. (2012). AutoTutor and affective autotutor: Learning by talking with cognitively and emotionally intelligent computers that talk back. *ACM Transactions on Interactive Intelligent Systems*, *2*(4). https://doi.org/10.1145/2395123.2395128
22. Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist*, *46*(1), 6–25.
23. Forbes-Riley, K., Rotaru, M., & Litman, D. J. (2008). The relative impact of student affect on performance models in a spoken dialogue tutoring system. *User Modeling and User-Adapted Interaction*, *18*(1–2), 11–43.
24. Forgas, J., Wyland, C., & Laham, S. M. (2006). Hearts and minds: An introduction to the role of affect in social cognition and behavior. *Affect in Social Thinking and Behavior*, *8*, 1.
25. Graesser, A. (2004). AutoTutor: A tutor with dialogue in natural language. *Behavior Research Methods, Instruments, & Computers*, *36*(2), 180–192. Retrieved from http://dx.doi.org/10.3758/BF03195563
26. Graesser, A. (2016). Conversations with AutoTutor Help Students Learn. *International Journal of Artificial Intelligence in Education*, *26*(1), 124–132. Retrieved from http://dx.doi.org/10.1007/s40593-015-0086-4
27. Graesser, A. C. (2008). Agent Technologies Designed to Facilitate Interactive Knowledge Construction. *Discourse Processes*, *45*(4–5), 298–322. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/01638530802145395
28. Graesser, A. C., Jackson, G. T., & McDaniel, B. (2007). AutoTutor holds conversations with learners that are responsive to their cognitive and emotional states. *Educational Technology*, 19–23.
29. Hassan, A., Mitchell, R., & Buriro, H. A. (2020). Changes in uses of salutations in British English. International research journal of management, IT and social sciences, 7(1), 197-204.
30. Hassan, A. (2016). Assimilation and incidental differences in Sindhi language. Eurasian Journal of Humanities, 2(1).
31. Hassan, A., Kazi, A. S., & Asmara Shafqat, Z. A. The Impact of Process Writing on the Language and Attitude of Pakistani English Learners. Asian EFL Journal, 27(4.3), 260-277.
32. Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education: Promises and implications for teaching and learning (pp.103-107)*. Retrieved from http://bit.ly/AIED-
33. Josep Seering, 2018. (2018). *In Lecture on 27th 2018,titled "Human-AI Interaction: an Introduction".*
34. Kim, C., Park, S. W., & Cozart, J. (2014). Affective and motivational factors of learning in online mathematics courses. *British Journal of Educational Technology*, *45*(1), 171–185.
35. Long, Y., & Aleven, V. (2013). Active learners: Redesigning an intelligent tutoring system to support self-regulated learning. *European Conference on Technology Enhanced Learning*, 490–495. Springer.
36. Luckin, R., Holmes, W., Griffiths, M., & Pearson, L. B. F. (2016). Intelligence Unsleashed. An argument for AI in Education. In *Pearson*. Retrieved from http://oro.open.ac.uk/50104/1/Luckin et al. - 2016 - Intelligence Unleashed. An argument for AI in Educ.pdf%0Ahttps://static.googleusercontent.com/media/edu.google.com/pt-BR//pdfs/Intelligence-Unleashed-Publication.pdf
37. Luckin Rosemary. (2010). *Re-designing learning contexts: Technology-rich, learner-centred ecologies*. Routledge.
38. Ma, W. (2014). Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis. *Journal of Educational Psychology*, *106*(4), 901–918. Retrieved from http://dx.doi.org/10.1037/a0037123
39. Mega, C., Ronconi, L., & De Beni, R. (2014). What makes a good student? How emotions, self-regulated learning, and motivation contribute to academic achievement. *Journal of Educational Psychology*, *106*(1), 121.
40. Mahmoudi, H. M., & Hassan, A. CHALLENGES AND ISSUES OF LANGUAGE USE BETWEEN MONOLINGUAL AND MULTILINGUAL SOCIETIES.
41. Manel, M., Hassan, A., & Buriro, H. A. (2019). Learners' Attitudes towards Teachers' switching to the mother tongue (The Case of Secondary school learners in Algeria). Indonesian TESOL Journal, 1(1), 9-26.
42. Mirza, Q., Pathan, H., Khatoon, S., Hassan, A., (2021). Digital Age and Reading habits: Empirical Evidence from Pakistani Engineering University. TESOL International Journal,16 (1), 210-136.
43. Munshi, A., Rajendran, R., Penn, J. O., Biswas, G., Baker, R. S., & Paquette, L. (2018). Modeling learners'

cognitive and affective states to scaffold srl in open-ended learning environments. *UMAP 2018 - Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*, 131–138. https://doi.org/10.1145/3209219.3209241

44. Munshi, Anabil, Rajendran, R., Ocumpaugh, J., Moore, A., & Biswas, G. (2018). *Studying the Interactions between Components of Self Regulated Learning in Open Ended Learning Environments*. International Society of the Learning Sciences, Inc.[ISLS].
45. ODE: The Oxford dictionary of English, (Oxford dictionaries online) Oxford: Oxford, & University Press. (2005). The Oxford dictionary of English.
46. Pekrun, R. (1992). *Expectancy-value theory of anxiety: In D. G Forgays, T.Sosnowski, & K Wrzesniewski (Eds.), Anxiety: Recent Developments in self-appraisal, psychophysiolgical and health research (pp.23-41). Washington, DC: Hemisphere.*
47. Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research. *Educational Psychologist*, *37*(2), 91–105.
48. Piaget, J., & Cook, M. (1952). *The origins of intelligence in children* (Vol. 8). International Universities Press New York.
49. Pintrich, P. R. (2000). The Role of Goal Orientation in Self-Regulated Learning. *Handbook of Self-Regulation*, 451–502. https://doi.org/10.1016/b978-012109890-2/50043-3
50. Rienties, B., & Rivers, B. A. (2014). Measuring and understanding learner emotions: Evidence and prospects. *Learning Analytics Review*, *1*, 1–28.
51. Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, *110*(1), 145.
52. Russell, S. J. (2016). *Artificial intelligence: a modern approach*. Retrieved from http://www.vlebooks.com/vleweb/product/openreader?id=none&isbn=9781292153971&uid=none
53. Shuman, V., & Scherer, K. R. (2014). Concepts and structures of emotions. In *International handbook of emotions in education* (pp. 23–45). Routledge.
54. Supriyatno, T., Susilawati, S., & Ahdi, H. (2020). E-learning development in improving students' critical thinking ability. Cypriot Journal of Educational Sciences, 15(5), 1099-1106.
55. Us Saqlain, N., Shafqat, A., & Hassan, A. (2020). Perception Analysis of English Language Teachers about Use of Contextualized Text for Teaching ESP. The Asian ESP Journal, 16(5.1), 275-299
56. Tempelaar, D. T., Niculescu, A., Rienties, B., Gijselaers, W. H., & Giesbers, B. (2012). How achievement emotions impact students' decisions for online learning, and what precedes those emotions. *The Internet and Higher Education*, *15*(3), 161–169.
57. Underwood, J., & Luckin, R. (2011). *What is AIED and why does Education need it?*
58. Vanlehn, K. (2007). When Are Tutorial Dialogues More Effective Than Reading? *Cognitive Science*, *31*(1), 3–62.
59. VanLehn, K. (2006). The Behavior of tutoring systems. *International Journal of Artificial Intelligence in Education*, *16*(3), 227–265.
60. Vygotsky, L. S. (1980). *Mind in society: The development of higher psychological processes*. Harvard university press.
61. Woolf, (2013). AI Grand Challenges for Education. *AI Magazine*, *34*(4), 66–84. Retrieved from http://search.proquest.com/docview/1490901631/?pq-origsite=primo
62. Woolf, Arroyo, I., Muldner, K., Burleson, W., Cooper, D. G., Dolan, R., & Christopherson, R. M. (2010). The effect of motivational learning companions on low achieving students and students with disabilities. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. https://doi.org/10.1007/978-3-642-13388-6_37
63. Zeidner, M. (2014). Anxiety in education. In *International handbook of emotions in education* (pp. 275–298). Routledge.
64. Zimmerman, B. J. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology*, *11*(4), 307–313. Retrieved from https://www.sciencedirect.com/science/article/pii/0361476X86900275
65. Zimmerman, B. J. (2000). *Attaining Self-Regulation-Chapter 2:A Social Cognitive Perspective*. Retrieved from http://dx.doi.org/10.1016/B978-012109890-2/50031-7