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Abstract

Self-Regulated Learning (SRL) is actually challenging modern online environments (e-learning platforms, MOOCs, exercise-based platforms, ...). A large emergent literature points out the need for empirical studies on approaches that can help to build tools for measuring and scaffolding SRL. This paper is a state of the art aiming to identify a set of key avenues to conduct a future experimental research on this theme. More importantly, we present the approaches of Open Learner Models, and knowledge Tracing through Bayesian Networks that offer promising insights to model student knowledge, measure SRL levels and provide appropriate interventions to foster student SRL skills.

Keywords: Self-Regulated Learning, Open Learner Models, Knowledge Tracing

1 Introduction

Although self-regulation has a long-time existence in the Education literature [1], it is a key challenge in modern online environments [2]. Indeed, with the advent of MOOCs, and the success of exercise-based platforms, large-scale online environments are becoming widespread, both in e-learning and in blended learning [3], and the success of such learning environments depends on the ability of the learners to take control on their own learning [4]. This learner's ability is referred to Self-Regulated Learning (SRL), which is known to have a good potential on autonomy development and maintaining motivation for learners [5]. SRL is also known to have a positive impact on academic achievements [6]. However, empirical studies aiming to support SRL at scale are lacking. There is a real need for analysing learner's activities for scaffolding SRL, especially in MOOCs [7; 8; 9]. Promoting SRL implies to provide students with interventions, defined as activities or events that can trigger student SRL development during a learning episode, for example during an online course [2].

Our main objective in this paper is to draw some insights on how to support successfully self-regulated learning at a large scale, and explore existing approaches that aim to estimate acquired skills levels and metacognitive levels about students to provide appropriate interventions. Our main research questions are the following:

1. What are the research requirements for SRL support at a large scale?
2. What are the main existing SRL supports that have been investigated?
3. What are the computational approaches for supporting SRL in online learning environments?

First of all, we introduce the concept of self-regulation and point out the need for empirical studies regarding SRL measurement and intervention. We present the approaches of Open Learner Models and Knowledge Tracing, which offer promising perspectives towards SRL. Finally, we discuss these avenues for a future research and we conclude on our interest in Bayesian modelling techniques to support personalization and self-regulated learning.

2 Self-Regulated Learning (SRL)

2.1 SRL Theory

Self-regulation is a well-established concept that includes the cognitive, metacognitive, behavioural, motivational and emotional/affective aspects of learning [10]. A typology of fourteen strategies of SRL that deal mainly with information processing, have been established, using a collection of qualitative data [1]. This includes cognitive strategies (Reviewing courses, organising information, memorising), metacognitive strategies (self-assessment, planning) and strategies for seeking additional information (using documentary resources, asking others for help). Another facet of self-regulation is to protect the intention to learn by regulating motivation, emotion and attention [11].

Self-regulation development or learning requires giving a certain level of autonomy to learners [5]. Autonomy is apprehended here from a constructivist perspective as "construction" and as "constructed" at the same time. This comprises a certain balance between prior knowledge and new knowledge, resulting from exchanges between the learner and his environment, and may be a product of his representations and confrontation with others" [12]. Self-Regulated learners have the ability to manage their own learning, and assume an active role in achieving their academic goals and controlling their learning process [4].

2.2 Research Requirements for Supporting SRL in Learning Environments

Self-regulated learning analysis has appeared as one of the main themes for future research in e-learning environments [2]. Many studies agree on the relevance of self-regulated learning in MOOCs, and point out the need for more empirical analysis of learners' activities [7; 8; 9]. Some of the main objectives of such research are to reduce the number of drop out students, to enhance learners' motivation and to increase learning success in MOOCs [9]. Indeed, in such learning environments, the lack of direct guidance from an instructor makes self-regulation very relevant [9].

Since learning environments supporting SRL place the learner as the controller of the learning process, these environments should provide tools for measuring and scaffolding SRL [4]. A scaffold or intervention is defined as an activity or event that can trigger SRL skills development of learners within an online course, while SRL strategy measures seek to establish SRL levels for learners [13; 4].

According to [14], self-regulation is divided into three different types: internal, behavioural and environmental. Different approaches described in the literature deal with internal self-regulation, i.e., affects, emotions, and motivation of learners, and behavioural self-regulation, i.e., learning behaviours. As highlighted by [14], there is a lack of works dedicated to analyse learning practices, leading to a kind of environmental self-regulation, i.e. to have an optimal educational environment for the success of learning.

A recent systematic review [2] makes a comprehensive synthesis, indicating that there is actually a noticeable shift from using tools that only measures SRL, to tools that go beyond the measurement to provide interventions. This review describes three trends of measurements that are used to promote SRL skills for learners in online learning environments: (i) SRL measured through Self-report tools, where learners reflect in a manual way, (ii) online measure of SRL based on learning data comprising a series of events, and (iii) measurement approaches that provide SRL interventions. This last trend is still emerging, and there is a lack of frameworks that help to integrate SRL measurement and interventions within data models [2].

Regarding the first research question "What are the research requirements for SRL support at a large scale?", we would say that more empirical work is needed for investigating how to provide personalised interventions and scaffolds to help learners in the SRL process. According to the literature, several approaches of interventions have been studied as shown in the next paragraph.

2.3 Existing Approaches for SRL Support and Interventions

Although a lack of empirical studies about how SRL can be supported in online learning environments, there is some evidence of different approaches that are used to provide SRL interventions. Three different approaches supporting learners to enhance their SRL skills were described [4]: (i) Learning Analytics (LA) through dashboard visualizations, enhancing learner activities through provision of suggested insights, (ii) Artificial Intelligent software agents, that offer assistive activity guidance to students, and (iii) learner feedback built from web-enabled prompts, facilitated through LA reports that assess learners' use of SRL strategies.

Other similar intervention approaches include [15]: (i) prompts such as questions, suggestions and short answer problems, (ii) feedbacks to trigger reflective activities and deepen learner understanding, and (iii) integrated support systems which are tools to support goals setting and SRL strategies. This also addresses the role of human factors including previous knowledge, cognitive and metacognitive abilities in adapting SRL approaches to best fit the individual learner needs.

According to [16], some existing studies provide partial SRL support, and rarely combine different approaches. For example, self-evaluation is already well supported in programming courses thanks to automated assessment tools, as well as goal setting and planning, while other strategies are not yet experimented [16].

Regarding the second research question "What are the main existing SRL supports that have been investigated ?", the most common approaches described in the literature, especially in online learning environments, include the use of Learning Analytics, prompts and feedback, and support systems for activity guidance, goal setting, planning and self-reflection.

2.4 Automatic Guidance VS Autonomy

Learning environments supporting SRL should provide students the ability to set up their learning goals, identify activities and strategies to achieve these goals, monitor and evaluate their progress [17]. Increasing students' autonomy supposes mixing self-reflection and explicit guidance when necessary. A standard solution to tailor the learning process to the learner needs include adaptive systems and Intelligent Tutoring Systems (ITS). While these systems are supposed to guide the learning process, SRL requires to give control to the learners. In other words, it is necessary to take a balance between automatic guidance and autonomy. Thus, adaptive learning systems and Intelligent Tutoring Systems should be modified to support SRL, that is to say, giving control to the learner and mixing self-reflection and explicit guidance when necessary. Moreover, adaptive systems and ITS led to the development of learner models [18]. Some particular learner models appeared as a complementary way to support SRL: Open Learner Models (OLM) [17]. Indeed, Open Learner Models are scrutable and might support self-reflection and metacognition as well as efficient, learner-controlled student modelling.

3 Learner Models to support SRL

3.1 Open Learner Models

A self-regulated learning system can be seen as a modified adaptive learning systems or ITS that supports SRL [17]. Providing a higher level of information could help learners to refine critical reflection and to make informed decisions. Indeed, the system has to provide personalized learning (recommending a next exercise, giving a simple list of relevant exercises, etc.), but also to encourage self-reflection, and to be able to justify interventions according to learners' goals and achievements. This is in relation to the concept of Open Learner Model (OLM), that goes beyond the learner model used in ITS and limited to a personalized learning perspective. While adaptive systems make use of learner information (e.g., knowledge state) by using a learner model to adapt a course or a system behaviour, the OLM approach pursues the idea of displaying learner information by making the learner model open to the learner and letting him choose the next steps [19]. In traditional ITS, control is given to the system which guides the learner in the learning process, but a self-regulated learner should take over the control on his own [17]. This is why the OLM approach is used to support the learner's reflection process by providing formative feedback on the learning process or even engaging negotiation with the learner [19]. Previous works on OLMs showed interesting effects on engagement with the learning content and the system [20]. For example, [21] showed that OLM helps learners to select better problems. Another example is reported in [22], on the Leaning Tracker tool [23] which provides a significant increased students' success, comprising a dashboard with visualisation comparing learners' own behaviour with successful learners' behaviour, in order to promote metacognition.

Personalised learning also comprises recommender systems that aim behavioural development by proposing specific activities and providing a structured environment. However, as noticed in the UNESCO report (2019) [24], it is important not to delegate decision-making to Artificial Intelligence (AI), but rather to serve the aims of humans. Learners should be able to make informed decisions by themselves. OLM allows the user (learner, teacher, peers and/or other stakeholders in the education process) to view the content of the learner model, in a human understandable form [25]. This focus on understandability is necessary if users are to be able to act appropriately on the learner model information [25]. To ensure the support is effective, the learner models must be interpretable by users [26], i.e., based on explainable models. As claimed in [27]: "the recommender system will not be transparent enough to adapt in an insightful way to the individual needs of students nor to the context of use". It is necessary to bring interdisciplinary expertise to develop explanatory learner models that provide interpretable and actionable insights in addition to accurate prediction, rather than relying on AI expertise alone [27].

A great variety of student modelling techniques have emerged based on student interactions in learning activities and knowledge measuring [28]. Knowledge Tracing is a popular technique used in ITS, in which modelling and predicting student knowledge is a fundamental task.

3.2 Knowledge Tracing

Knowledge Tracing is a standard for inferring student knowledge [29]. It is the task of modelling student knowledge over time, so that we can accurately predict how students will perform on future interactions. This means that resources can be suggested to students based on their individual needs, and content which is predicted to be too easy or too hard can be skipped or delayed. The problem of knowledge tracing is inherently difficult since human learning is complex, and has been heavily studied within the intelligent tutoring community to find appropriate and rich models [30]. In this section we describe two main approaches that are used to build student models, with their related pros and cons: Bayesian Knowledge Tracing (BKT) [31], which is the most popular one and Deep Knowledge Tracing (DKT) [30], which emerges as an alternative to BKT.

Bayesian Knowledge Tracing

A popular approach for student modelling is Bayesian Knowledge Tracing (BKT), using simple Bayesian Networks [32], or mostly Dynamic Bayesian Networks, having the potential to increase the representational power of the student model and improve prediction accuracy [33; 34; 35; 36]. BKT models a learner's knowledge state as a set of binary variables [31], each of which represents understanding or non-understanding of a single concept. For instance, when making a prediction, the model is provided with the tag of the exercise being answered, and must predict whether the student will get the exercise correct, or false. This binary representation of students' understanding or skills is seen as the main limitation of BKT [30]. However, this limitation can easily be lifted, since Bayesian networks are not restricted to binary random variables [37].

Knowledge representation. The selection of Bayesian Networks to model students' learning is justified by several reasons in the literature. First, such methods are used in different domains in decision making [37], and in a wide variety phenomenon in ITS including models of students' knowledge [38]. Bayesian Networks can accommodate both empirical and theoretical knowledge [39]. More specifically, this modelling approach can take advantage of both empirical and theoretical knowledge of SRL in large-scale online environments [40]. Bayesian Networks are defined with a directed acyclic graph between random variables that encode the probabilistic dependencies between variables, and a set of conditional probability distributions (the parameters) that encode the strength of these dependencies. Both the structure and the conditional dependencies can be learned using a variety of possible algorithms [37] or specified by hand. At the intersection between Knowledge representation and Machine Learning in Artificial Intelligence, these models can be iteratively built from knowledge elicitation [41; 42] to learning from data through successive refinements [43].

Interpretable models. Bayesian Networks also have other important advantages derived from their typology as probabilistic graphical models. One is that we can visualize the interaction of variables and have a better "understanding" of the process, for example, when the dependencies between the random variables have been defined in a causal way [41]. In fact, thanks to their graphical dimension and their causality expressiveness, Bayesian Networks are de-facto "interpretable" [44], i.e., can be easily "inspected" and "understood" by experts or users.

Deep Knowledge Tracing

Recent studies showed improvement over state of the art performance on dynamic probabilistic models. Models supported by Recurrent Neural Networks (RNNs) have been applied to the Knowledge Tracing Task, leading to the concept of Deep Knowledge Tracing (DKT), showing predictive power superior to BKT [30; 45]. RNNs were applied to data from Khan Academy's online courses to predict students' performance [30]. An improvement of this work is performed later on a dataset from the MOOC Hour of Code, in which data is structured in the form of program submissions, instead of a binary form [45]. The deep learning model trains on a student's history of past code submissions and predicts the student's performance on the next exercise [45]. These studies highlighted a rich property of RNNs, such as their ability to use information from an input in a prediction at a much later point in time. The learned model does not need expert annotations (it can learn concept patterns on its own) and it can operate on any student input that can be vectorized. However, one disadvantage of RNNs over the previous Bayesian Network based approaches, which was highlighted [30], is that RNNs require large amounts of training data, and so are not well suited to a small classroom environment. A more recent work [29] explored a novel method to improve the prediction process by combining Bayesian Neural Network with DKT, in order to better model students' learning and track the process of students' knowledge acquisition. This approach showed performances on modelling feature-rich students' behaviour data, preventing overfitting, enhancing the generalisation ability of the model, and accelerating the convergence speed of the model [29].

4 Discussion and Conclusions

SRL aims both increasing students' autonomy and guiding their own learning while providing personalised and necessary support. Based on that, one approach to face the challenges of measuring SRL in Open Online Environments and building personalised interventions is to combine the OLM and Knowledge Tracing approaches. To provide effective SRL support, student models have to be interpretable by users [26]. Providing explanations on learning process stimulate reflection on metacognition, beyond activity recommendations.

From the presented student modelling approaches, we would say that DKT seems to be an improvement over BKT with regard to the prediction performance [30; 45], however BKT offers more valuable insights on how explanations are communicated to the end user to be understandable [44]. DKT is also empirically well suited in case of large amounts of data, having high semantic complexity and manually choosing features is tedious or insufficient [45]. In addition, from the approach that combines Bayesian neural network with DKT [29], we would say that DKT may not be sufficient on its own and needs to take advantage from Bayesian Networks, although it provides a high prediction performance. Since SRL needs theoretical knowledge to be tracked and measured, we could expect a set of human input and expert knowledge needed to feed the learner model, and so Bayesian Networks would be more suited. Moreover, existing work [40] has shown promise in being able to predict SRL behaviours early into interaction, using Bayesian Networks. This may include features related to the self-regulation process, such as planning and monitoring behaviours [40].

Regarding our ultimate research question "What are the computational approaches for supporting SRL in online learning environments?", applying Bayesian modelling techniques would be a sound approach towards supporting SRL in Open Online Environments, and so at scale. This can include SRL measures and personalised interventions. Bayesian Networks (or Dynamic ones) offer interesting insights for acquiring and updating learners' models as OLMs, about cognitive and metacognitive skills and progression of learners. In a future work, we will attempt to test this approach on data from large populations, to conduct experimental research. This will include data corpus resulting from available large scale learning platforms comprising MOOCs series (available on FUN and Edx platforms) and an exercise-based platform (France IOI).

Adopting a design-based research approach is necessary to tackle empirical analysis of learner activities [46]. This will enable to combine two complementary research focuses with feedback from real experiments (technical and social approach). In such context, conducting an experimental study necessitate an interdisciplinary research.

Acknowledgements

Based on this preliminary work, future research experiments will be conducted as part of the Xcale project (2021-2024), funded by the French National Research Agency (ANR)/AAPG 2020.

References

[1] B. J. Zimmerman and M. M. Pons, "Development of a structured interview for assessing student use of self-regulated learning strategies," *American educational research journal*, vol. 23, no. 4, pp. 614–628, 1986.

[2] E. Araka, E. Maina, R. Gitonga, and R. Oboko, "Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—systematic review (2008–2018)," *Research and Practice in Technology Enhanced Learning*, vol. 15, no. 1, pp. 1–21, 2020.

[3] D. Light and E. Pierson, "Increasing student engagement in math: The use of khan academy in chilean classrooms," *International Journal of Education and Development using ICT*, vol. 10, no. 2, pp. 103–119, 2014.

[4] E. Araka, E. Maina, R. Gitonga, and R. Oboko, "A conceptual model for measuring and supporting self-regulated learning using educational data mining on learning management systems," in *2019 IST-Africa Week Conference (IST-Africa)*, pp. 1–11, IEEE, 2019.

[5] D. H. Schunk and B. J. Zimmerman, *Motivation and self-regulated learning: Theory, research, and applications*. Routledge, 2012.

[6] B. J. Zimmerman, "Self-regulated learning and academic achievement: An overview," *Educational psychologist*, vol. 25, no. 1, pp. 3–17, 1990.

[7] P. De Barba, G. E. Kennedy, and M. Ainley, "The role of students' motivation and participation in predicting performance in a mooc," *Journal of Computer Assisted Learning*, vol. 32, no. 3, pp. 218–231, 2016.

[8] J. Riel and K. A. Lawless, "Developments in mooc technologies and participation since 2012," in *Encyclopedia of Information Science and Technology, Fourth Edition*, pp. 7888–7897, IGI Global, 2018.

[9] C. Alario-Hoyos, I. Estévez-Ayres, M. Pérez-Sanagustín, C. D. Kloos, and C. Fernández-Panadero, "Understanding learners' motivation and learning strategies in moocs," *The International Review of Research in Open and Distributed Learning*, vol. 18, no. 3, 2017.

[10] E. Panadero, "A review of self-regulated learning: Six models and four directions for research," *Frontiers in psychology*, vol. 8, p. 422, 2017.

[11] L. Cosnefroy, "Se mettre au travail et y rester: les tourments de l'autorégulation," *Revue française de pédagogie. Recherches en éducation*, no. 170, pp. 5–15, 2010.

[12] J. Eneau and S. Simonian, "Un scénario collaboratif pour développer l'apprentissage d'adultes, en ligne et à distance," *Recherche et formation*, no. 68, pp. 95–108, 2011.

[13] K. Triquet, J. Peeters, and K. Lombaerts, "Self-regulated learning online: Empirical foundations," *Promotion and Evaluation for Teacher Professional Development Contributing SRL Part of Deliverable D*, vol. 1, 2017.

[14] A. Jézégou, "Se former à distance: regard sur les stratégies d'autorégulation environnementale d'étudiants adultes," *Savoirs*, no. 3, pp. 79–99, 2010.

[15] J. Wong, M. Baars, D. Davis, T. Van Der Zee, G.-J. Houben, and F. Paas, "Supporting self-regulated learning in online learning environments and moocs: A systematic review," *International Journal of Human–Computer Interaction*, vol. 35, no. 4-5, pp. 356–373, 2019.

[16] R. Garcia, K. Falkner, and R. Vivian, "Systematic literature review: Self-regulated learning strategies using e-learning tools for computer science," *Computers & Education*, vol. 123, pp. 150–163, 2018.

[17] A. Nussbaumer, E.-C. Hillemann, C. Gütl, and D. Albert, "A competence-based service for supporting self-regulated learning in virtual environments.," *Journal of Learning Analytics*, vol. 2, no. 1, pp. 101–133, 2015.

[18] A. T. Corbett, K. R. Koedinger, and J. R. Anderson, "Intelligent tutoring systems," in *Handbook of human-computer interaction*, pp. 849–874, Elsevier, 1997.

[19] S. Bull and J. Kay, "Open learner models," in *Advances in intelligent tutoring systems*, pp. 301–322, Springer, 2010.

[20] J. Guerra, R. Hosseini, S. Somyurek, and P. Brusilovsky, "An intelligent interface for learning content: Combining an open learner model and social comparison to support self-regulated learning and engagement," in *Proceedings of the 21st international conference on intelligent user interfaces*, pp. 152–163, 2016.

[21] A. Mitrovic and B. Martin, "Evaluating the effect of open student models on self-assessment," *International Journal of Artificial Intelligence in Education*, vol. 17, no. 2, pp. 121–144, 2007.

[22] D. Lee, S. L. Watson, and W. R. Watson, "Systematic literature review on self-regulated learning in massive open online courses," *Australasian Journal of Educational Technology*, vol. 35, no. 1, 2019.

[23] D. Davis, G. Chen, T. Van der Zee, C. Hauff, and G.-J. Houben, "Retrieval practice and study planning in moocs: Exploring classroom-based self-regulated learning strategies at scale," in *European conference on technology enhanced learning*, pp. 57–71, Springer, 2016.

[24] M. Yoko and B. Éric, eds., *Rethinking pedagogy: exploring the potential of digital technology in achieving quality education*. UNESCO, 2019.

[25] S. Bull and J. Kay, "Smili: A framework for interfaces to learning data in open learner models, learning analytics and related fields," *International Journal of Artificial Intelligence in Education*, vol. 26, no. 1, pp. 293–331, 2016.

[26] C. Conati, K. Porayska-Pomsta, and M. Mavrikis, "Ai in education needs interpretable machine learning: Lessons from open learner modelling," *arXiv preprint arXiv:1807.00154*, 2018.

[27] C. P. Rosé, E. A. McLaughlin, R. Liu, and K. R. Koedinger, "Explanatory learner models: Why machine learning (alone) is not the answer," *British Journal of Educational Technology*, vol. 50, no. 6, pp. 2943–2958, 2019.

[28] R. Bodily, J. Kay, V. Aleven, I. Jivet, D. Davis, F. Xhakaj, and K. Verbert, "Open learner models and learning analytics dashboards: a systematic review," in *Proceedings of the 8th international conference on learning analytics and knowledge*, pp. 41–50, 2018.

[29] L. Donghua, J. Yanming, Z. Jian, W. Wufeng, and X. Ning, "Deep knowledge tracing based on bayesian neural network," in *International Conference on Intelligent and Interactive Systems and Applications*, pp. 29–37, Springer, 2019.

[30] C. Piech, J. Bassen, J. Huang, S. Ganguli, M. Sahami, L. J. Guibas, and J. Sohl-Dickstein, "Deep knowledge tracing," in *Advances in neural information processing systems*, pp. 505–513, 2015.

[31] A. T. Corbett and J. R. Anderson, "Knowledge tracing: Modeling the acquisition of procedural knowledge,"

User modeling and user-adapted interaction, vol. 4, no. 4, pp. 253–278, 1994.

[32] E. Millán, T. Loboda, and J. L. Pérez-De-La-Cruz, "Bayesian networks for student model engineering," *Computers & Education*, vol. 55, no. 4, pp. 1663–1683, 2010.

[33] J. P. Rowe and J. C. Lester, "Modeling user knowledge with dynamic bayesian networks in interactive narrative environments," in *Sixth Artificial Intelligence and Interactive Digital Entertainment Conference*, 2010.

[34] Z. A. Pardos and N. T. Heffernan, "Modeling individualization in a bayesian networks implementation of knowledge tracing," in *International Conference on User Modeling, Adaptation, and Personalization*, pp. 255–266, Springer, 2010.

[35] T. Käser, S. Klingler, A. G. Schwing, and M. Gross, "Beyond knowledge tracing: Modeling skill topologies with bayesian networks," in *International conference on intelligent tutoring systems*, pp. 188–198, Springer, 2014.

[36] Y. Cui, M.-W. Chu, and F. Chen, "Analyzing student process data in game-based assessments with bayesian knowledge tracing and dynamic bayesian networks," *JEDM— Journal of Educational Data Mining*, vol. 11, no. 1, pp. 80–100, 2019.

[37] E. Alpaydin, *Introduction to machine learning*. MIT press, 2020.

[38] R. S. Baker, A. T. Corbett, and V. Aleven, "More accurate student modeling through contextual estimation of slip and guess probabilities in bayesian knowledge tracing," in *International conference on intelligent tutoring systems*, pp. 406–415, Springer, 2008.

[39] C. Conati and H. Maclaren, "Empirically building and evaluating a probabilistic model of user affect," *User Modeling and User-Adapted Interaction*, vol. 19, no. 3, pp. 267–303, 2009.

[40] J. Sabourin, B. Mott, and J. Lester, "Utilizing dynamic bayes nets to improve early prediction models of self-regulated learning," in *International Conference on User Modeling, Adaptation, and Personalization*, pp. 228–241, Springer, 2013.

[41] L. C. Van der Gaag, S. Renooij, C. L. Witteman, B. M. Aleman, and B. G. Taal, "Probabilities for a probabilistic network: a case study in oesophageal cancer," *Artificial Intelligence in medicine*, vol. 25, no. 2, pp. 123–148, 2002.

[42] S. Renooij, "Probability elicitation for belief networks: issues to consider," *The Knowledge Engineering Review*, vol. 16, no. 3, pp. 255–269, 2001.

[43] U. B. Kjærulff and A. L. Madsen, "Probabilistic networks for practitioners–a guide to construction and analysis of bayesian networks and influence diagrams," *Department of Computer Science, Aalborg University, HUGIN Expert A/S*, 2006.

[44] C. Lacave and F. J. Díez, "A review of explanation methods for bayesian networks," *The Knowledge Engineering Review*, vol. 17, no. 2, pp. 107–127, 2002.

[45] L. Wang, A. Sy, L. Liu, and C. Piech, "Deep knowledge tracing on programming exercises," in *Proceedings of the Fourth (2017) ACM Conference on Learning@ Scale*, pp. 201–204, 2017.

[46] T. Štemberger and M. Cencic, "Design based research: The way of developing and implementing.," *World Journal on Educational Technology: Current Issues*, vol. 8, no. 3, pp. 180–189, 2016.