A Framework for exploring the impact of tutor practices on learner self-regulation in online environments

Madiha Khan-Galaria[1], Mutlu Cukurova[2] and Rose Luckin[3]

[1] University College London, United Kingdom
m.khan.16@ucl.ac.uk
[2] University College London, United Kingdom
m.cukurova@ucl.ac.uk
[3] University College London, United Kingdom
r.luckin@ucl.ac.uk

Abstract. There is increasing interest in the conceptualization of self-regulated learning (SRL) as a dynamic process which unfolds over the course of a learning activity. This is partly because this conceptualization could potentially be operationalized and used as the basis for AI and analytics tools which monitor and scaffold SRL in real-time. However, while there is an abundance of research on theories of SRL, little research explicitly reviews and operationalizes such theoretical considerations. Work is needed to develop frameworks for the practical applications of fundamental SRL theories, helping researchers move from conceptual considerations to operationalization in real world settings. In this paper, we propose a theoretically grounded framework for investigating SRL in the context of online tutoring for upper primary school learners. SRL is interpreted as a social learning construct, and the framework proposed is designed to investigate the influence of tutor practices on the development of learners' SRL. We present the results of a pilot study that explored the applicability of the framework.

Keywords: Self-regulated learning, online tutoring, Winne and Hadwin model, tutor practices, metacognition, virtual classroom environment, process mining

1 Introduction

There is increasing interest in the conceptualization of self-regulated learning (SRL) as a dynamic process which unfolds over the course of a learning activity. Mapping out SRL as a dynamic process is of interest, as it may provide opportunities for real time monitoring, evaluation and support of SRL in online learning environments. For example, there may be opportunities for intelligent tools which support tutors in real time as they scaffold learner self-regulation. However, there is limited research on frameworks, which are both theoretically grounded (Matcha et al 2019), and sufficiently granular to investigate self-regulation in online learning environments.

To address this need, this paper proposes a framework to investigate the impact of tutor practices on learner self-regulation in online environments. Specifically, we focus on an online tutoring environment in which human tutors teach primary school learners (aged 10 years) on a one to one basis, using an interactive whiteboard and tools. We identify signifiers from natural language dialogue between tutor and learner, and explore the applicability of the framework in a pilot study. Our initial findings are not intended to be generalized to a population, but aim to build on research exploring how to operationalize SRL theoretical models in online environments (Hadwin et al 2007).

2 Framework development

The framework has been developed through a two stage, mixed methods approach. Firstly, an established theoretical model is adapted to apply to the online tutoring environment. In the second stage, we use a data driven approach to refine the framework.

The framework developed in this research required a granular, fluid model of SRL which could be applied to real world settings, and use online data. After the review of available theoretical models [Winne & Hadwin 1998, Pintrich 2000a, Zimmerman 2000), the Winne and Hadwin (1998) model was identified as a suitable model.

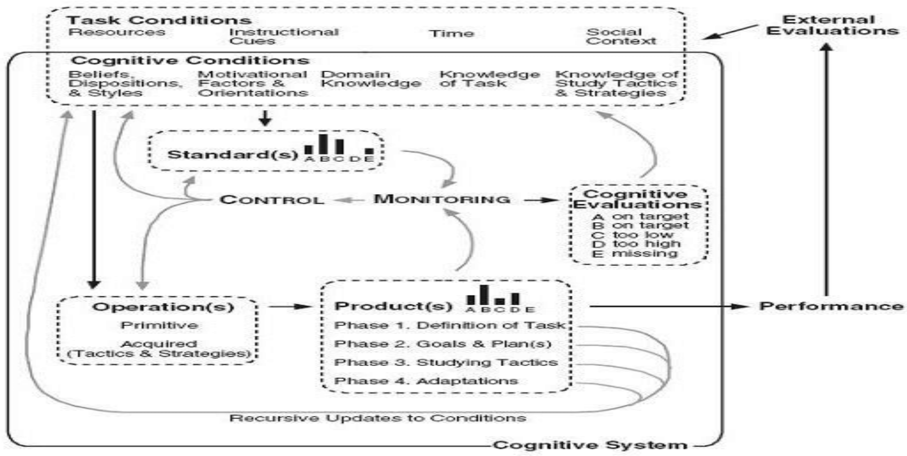

Fig. 1. Winne and Hadwin model (Winne & Hadwin 1998)

The Winne and Hadwin model was selected as it is highly granular and suited to the analysis of fine-grained data that is generated from online environments. Further, the model synthesizes all the various components of SRL from the literature into a heuristic framework (Azevedo et al 2010, Bannert et al 2014).

The Winne and Hadwin model was adapted to fit our research purposes, namely to investigate the impact of tutor practices on SRL. The model recognizes tutor practices as an external condition impacting learner SRL. Our framework builds on this, and interprets each sub-component to identify tutor practices which may scaffold learner SRL. Following the adaptation of the model, online tutoring sessions were observed to identify fine grained actions. For our empirical work, we partnered with an industrial supplier named Third Space Learning (TSL), which delivers maths tutoring for primary school children aged 10 years old. Learners and tutors log into a shared online environment, and the learner works through a pre-designed online set of questions, with the guidance of a human tutor on an interactive whiteboard. The data available for analysis includes the online resources, natural language dialogue audio between tutor and student, logfile and whiteboard data. TSL sessions were filtered by topic, and the recordings of 50 randomly selected sessions were observed. Fine grained actions that could be observed from the data were mapped to the theoretical framework. This exercise illustrated that there were a number of tutor actions aimed at promoting certain types of engagement by learners which were not yet captured. For example, the theoretical framework did not distinguish between tutors who lectured versus prompting learners to construct meaning. The 'Operations' component was thus broadly defined to refer to the nature of tutor-learner engagement, characterized using the Chi & Wyle ICAP framework (Chi & Wylie 2014). The final framework is presented in table 1.

Table 1. Framework for exploring tutor practices that influence SRL in online environments

Model	**Operational definition of sub-components**	**Examples of signifiers**
Conditions	Tutor actions and utterances scaffolding learner mindset e.g. specific praise)	Tutor utterances:*' 'Well done for persevering'.* Tutor awarding effort points, pictures and emojis.
Operations	Directive engagement - Tutor instructs or explains	Tutor utterances "*To solve this problem, you need to…*
	Active engagement -Tutor prompts learner to physically manipulate the content	Tutor utterances: "*Please underline the key words"*
	Constructive engagement -Tutor prompts learner to construct meaning. The question style can be closed ended/narrow or open ended	Tutor utterances ('narrow')*: 'What is x plus y'?" "Is it a or b"* ('open ended'')*: "How did you work this out")*
	Interactive engagement	A dialogue where both the learner and the tutor have at least two turns with constructive utterances
Products	Tutor prompts learner to try to understand the question, set goals and plan.	Tutor utterances: "*What does this question mean?" "How will you do this"?*
	Tutor prompts learner to use of study tactic, or to make adaptations to SRL products.	Tutor utterances*: "What method can we use to do this? "Is there a different way of doing this?"*
Evaluation against Standards	Tutor prompts learner to monitor cognition, meta-cognition and affect	Tutor utterances: *"How do you feel about this topic?" "Do you need help?"*

3 Pilot study

We tested the applicability of the framework by applying it to data gathered from tutors manually classified as 'high ranking' and 'mid ranking'. 180 tutors were ranked using student learning outcomes (30%), tutor evaluation test scores (30%), human evaluator scores (30%), and student qualitative ratings for tutors (10%). Tutors in the top ten percentile i.e. with a rank between 1-18, and tutors in the 45th to 55th percentile i.e. with a rank between 81 and 99 were randomly selected. 121 minutes of audio and whiteboard data from 21 sessions for the selected tutors was extracted and manually tagged using the framework. The data collected was allocated into time bins, as per table 1:

Table 2. Allocation of session data into time bins

Time bins (mm. ss)	0.00-2.00	2.01-4.00	4.01-6.00	6.01-8.00	8.01-10.33	Total
High ranking tutors (11 sessions)	20.00	20.58	13.04	04.40	02.25	60.31
Mid ranking tutors (10 sessions)	20.00	18.02	10.07	07.09	06.25	61.43

We plotted the tutor practices against the time bins, with the size of the bubble being the average relative frequency of each behavior. Figure 2 shows the results for high ranking and mid ranking tutors. We found that high ranking tutors were more likely to demonstrate practices scaffolding open-ended constructive engagement, such as prompting self-explanation. High ranking tutors embedded monitoring throughout the session, while mid ranking tutors used this practice less regularly. We also found that tutor practices boosting learner mindset (e.g. specific praise) were more prominent amongst high ranking tutors, with a relative frequency of 0.42 for all high-ranking tutors, versus 0.28 for all mid ranking tutors.

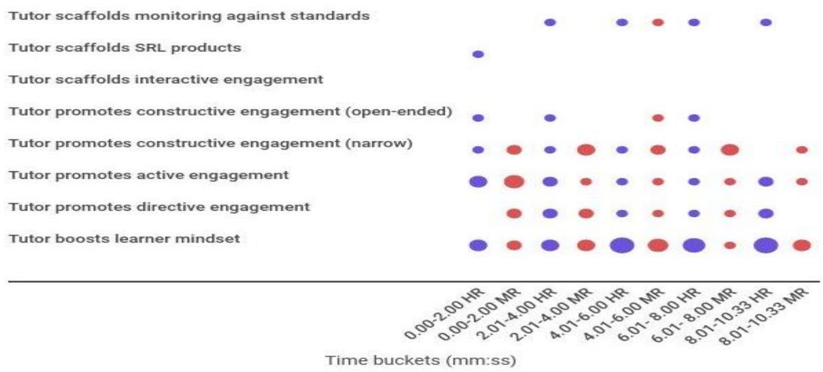

Fig. 2. Average relative frequency of high-ranking tutor practices (purple) vs mid-ranking tutor practices (red)

The next stage of work will refine the framework to include non-audio traces of SRL behaviour (e.g. use of pointer). We will build the data sample to include low ranking tutors, prior to applying modelling and analytics such as process mining and decision trees. We will examine whether we can effectively use audio and non-audio traces to identify tutor practices scaffolding SRL, and the impact of contextual and macro factors on these practices. We will also analyse the implications of our work for operationalizing SRL in online tutoring environments, and the potential for building intelligent tools, which support human tutors in fostering learner SRL.

References

1. Azevedo, R., Moos, D., Johnson, A., & Chauncey, A. (2010) Measuring Cognitive and Metacognitive Regulatory Processes During Hypermedia Learning: Issues and Challenges, Educational Psychologist, 45:4, 210-223, DOI: 10.1080/00461520.2010.515934
2. Bannert, M., & Reimann, P., & Sonnenberg, C. (2014) Process mining techniques for analysing patterns and strategies in students' self-regulated learning. Metacognition Learning (2014) 9:161–185
3. Behrens, J., Dicerbo, K. (2014) Harnessing the Currents of the Digital Ocean. Chapter three, Learning analytics: from research to practice / Johann Ari Larusson, Brandon White ;New York, Springer 2014
4. Chi, M. T. H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. Educational Psychologist, 49(4), 219–243
5. Cukurova, M, Avramides, K, Spikol, D, Luckin, R, and Mavrikis, M. An Analysis Framework for Collaborative Problem Solving in Practice-based Learning Activities: A Mixed-method Approach (2016): In: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge. (pp.. 84-88). ACM: New York, NY, USA. (2016)
6. Duncan, G.J., Dowsett, C.J., Claessens, A., Magnuson, K., Huston, A.C., Klebanov, P., Pagani, L.S., Feinstein, L., Engel, M., Brooks-Gunn, J., Sexton, H., Duckworth, K. and Japel, C. (2007) School readiness and later achievement. Developmental Psychology, 43(6), 1428–46
7. Hadwin, A., Nesbit, J., Jamieson Noel, D., Code, J., Winne, P. (2007) Examining trace data to explore self-regulated learning. Metacognition Learning (2007) 2:107–124
8. Pintrich, P. R. (2000a). Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. Journal of Educational Psychology, 92, 544–555
9. Juhanak, L., Zounek, J., Rohlikova, L. (2019). Using Process Mining to analyse students quiz taking behaviour patterns in a Learning Management System. Computers in Human Behaviour (2019) 496-506
10. Larusson, J., White, B. (2014). Learning analytics: from research to practice. Introduction, p1-12 ; New York, Springer
11. Matcha W., Uzir, N., Gasevic, D., Pardo, A. (2019). A systematic review of empirical studies on Learning Analytics Dashboards: A Self-Regulated Learning perspective. IEEE Transactions on Learning Technologies. (2019)
12. McClelland, M., Morrison, F.J. and Holmes, D.L. (2000) Children at risk for early academic problems: The role of learning-related social skills. Early Childhood Research Quarterly, 15, 307–29
13. Pardo, A. (2014). Designing Learning Analytics Experiences. In: J. Larusson, B. White eds *Learning analytics: from research to practice*; New York, Springer. Chapter three
14. Sedrakyan, G., De Weerdt., J, Snoeck., M. (2016). Process Mining enabled feedback: Tell me what I did wrong vs, tell me how to do it right. Computers in Human Behaviour 57 (2016) 352-376
15. Van der Aalst, W. (2012). Process mining: Overview and opportunities. ACM Trans. Manage. Inf. Syst. 3, 2, Article 7 (July 2012)
16. Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. Graesser (Eds.), Metacognition in educational theory and practice (pp. 277-304). Hillsdale, NJ: Lawrence Erl
17. Zimmerman, B.J. (2000). Attaining self-regulation, a socio-cognitive perspective. Handbook of self regulation 2000