Utilising a Virtual Learning Assistant as a Measurement and Intervention Tool for Self-Regulation in Learning

Eduard Pogorskiy
School of Education
Durham University
Durham, United Kingdom
eduard.pogorskiy@durham.ac.uk

Jens F. Beckmann
School of Education
Durham University
Durham, United Kingdom
j.beckmann@durham.ac.uk

Srećko Joksimović
School of Education
University of South Australia
Adelaide, Australia
srecko.joksimovic@unisa.edu.au

Vitomir Kovanović
School of Education
University of South Australia
Adelaide, Australia
vitomir.kovanovic@unisa.edu.au

Robert West
Department of Behavioural Science and Health
University College London
London, United Kingdom
robert.west@ucl.ac.uk

***Abstract*—Online learning and massive open online courses are widely used in engineering and technology education. Engineering next-generation learning requires overcoming the potential constraints of online learning environments which necessitate higher levels of self-regulation than traditional classroom settings. This particular requirement demands that learners allocate their cognitive, metacognitive, affective and motivational resources to meet this need. Lack of self-regulation can affect learners' engagement with the course content, resulting in sub-optimal learning outcomes or failure to complete the course. This paper reports on the design of a virtual learning assistant and its implementation in online learning activities. This paper outlines the virtual assistant's use as a data collection tool and, further, proposes that the virtual learning assistant has the potential to be used as an assessment tool for self-regulatory skills, and as an intervention tool to support online learners' self-regulation in online learning.**

Keywords—MOOCs, online learning, self-regulation, adult learning, virtual learning assistant

I. Introduction

Online learning and massive open online courses (MOOCs) provide new opportunities for spreading education in engineering worldwide. Courses that fall within the fields of computer science, physical science and engineering are traditionally widely represented on massive open online course platforms, such as Coursera; these topics account for nearly a third of all offered courses [1]. However, learners have been found to experience different outcomes from the same online courses and learning environments, depending on individual differences. These variables include cultural background [2][3], country of origin [4], the level of incentive and insufficient prior knowledge [5]. Online learning environments have the potential to overcome barriers to accessing learning opportunities typically associated with traditional learning offers, yet they come with their specific challenges. Online courses tend to be primarily frequented by adult learners, seem to exert less social pressures, offer limited opportunities for interactions with course instructors (particularly in massive open online courses), are highly flexible in terms of studying hours and physical spaces, and allow for a wide availability of alternative behaviour options and possible distractions [6]. The characteristics of online learning require that learners are equipped with higher self-regulatory skills in comparison to traditional classroom settings. The nature of online learning environments make it more challenging for students to allocate their cognitive, metacognitive, affective and motivational resources to a learning task. Online learning environments provide more chances for failure, and, in comparison to their on-campus counterparts, online learners require greater levels of resistance to overcome such failures. Lack of self-regulatory skills, then, tend to cause course dropout, can affect a student's engagement with course content, and their academic performance.

This paper will discuss the design of a virtual learning assistant which consists an extension to the Chrome web browser, a server-side application with a database that consists of trace data, and a web interface with learning analytics, and it has the potential to be utilised as an instrument to support self-regulated learning (SRL). The focus of this work is to give an overview of the virtual learning assistant from the perspective of data collection regarding the self-regulation of learning. This paper also will suggest that a virtual learning assistant has the potential to be utilised in two additional ways: first, as an assessment tool regarding the motivational, cognitive, affective and metacognitive components of self-regulated learning, and, second, as an intervention tool which could help learners to develop their self-regulatory skills, and to compensate for any issues with self-regulation.

II. Related Work

A. Self-Regulated Learning

Self-regulation in learning has become a key concept within educational research literature [7][8]. Over the last decade, self-regulated learning has increasingly been understood as an overarching construct, uniting the variety of variables that underlie learning processes. The majority of conceptual frameworks applied to self-regulated learning are derived from two main theoretical streams: social-cognitive and information-processing. Both theoretical streams have common characteristics in terms of stages and phases of SRL, and are supported by evidence. Self-regulation is built upon cognitive, metacognitive, motivational and affective components of the learning process. Despite differential nuances between the theoretical constructs among existing SRL models [9]–[14], existing theories and empirical evidence tend to agree in their conceptualisation of SRL as a dynamic process constituted from a cyclical set of phases and components influenced by, within, and between learners, tasks and contexts specificity. These phases and components of SRL can be summarised as: planning and goal setting, self-monitoring and self-control, and self-evaluation, or, alternatively: preparatory, performance and appraisal phases [15], and cognitive, metacognitive, motivational, and affective components of SRL.

B. Self-Regulated Learning Assessment

Due to the increasing importance of SRL to learning processes and performance, and given that SRL is considered as an educational skill which can be developed [7] it is imperative to obtain a reliable and valid measurement toolset to capture SRL and any changes in SRL as the effect of interventions. Self-regulated learning can be assessed using two potential approaches: aptitudes and event measures [16]. The former involves the application of self-reports, such as self-regulation questionnaires and interviews [17][18]. The latter is based on behaviour data and consists of fine-grained measures, such as microanalytic [16], trace data [19] and data mining methods [20]. However, aptitude measures do not tend to closely correspond to event data, and it is beneficial to utilise both approaches in order to avoid issues relating to the validity and reliability of an assessment tool.

C. Self-Regulated Learning Interventions

SRL is a complex skill that can be developed by the learner over time. As such, one of the primary needs for studies of SRL is a fine-grained longitudinal research model that employs an experimental design that can be run over an extended period of time in order to track changes in SRL skills and to provide insight into how SRL development might occur, particularly, in adults [21][22]. As indicated in [15], among the most promising educational interventions of SRL are: 1) providing teachers with training on SRL theory and models, 2) teaching SRL at different educational levels, 3) creating classroom environments that maximise SRL, and 4) developing learners' SRL skill. The latter appears to be most promising in terms of online learning environments, as this option is independent of teachers, classroom availability, and learners' involvement in formal education.

Existing literature suggests various different methods for developing self-regulation. Previous studies have attempted a variety of interventions to improve students' ability to self-regulate during online learning experiences. These have included providing externally generated feedback using hypermedia [23], instructing self-regulated learning strategies to online learners [24], and providing interventions to prevent procrastination behaviour using Android Wear [25]. Relatively few studies, however, have attempted to utilise web-browser extensions in educational research. Among these few attempts are nStudy [26] and NoteMyProgress [27]. Both studies used tools designed to gather large sets of educational data to test conceptual models and theories, and to support self-regulation in massive open online courses.

III. Features and Capabilities

This paper provides an overview of a virtual learning assistant. The virtual assistant aims to help learners to utilise the opportunities provided by online learning more effectively. To this end, the assistant was developed with the aim to help online learners to manage their time more effectively and to prevent procrastination. This tool consists of an extension to the Chrome web browser, a server-side application with a database that consists of trace data, and a web interface with learning analytics.

A web browser extension is a plug-in that extends the functionality of a web browser. Users of the Chrome web browser can download and install extensions. The extension was developed for the Chrome browser, and it extends the functionality of the browser. The extension allows for the collection of data on its users' web sessions, and interacts with the user through pop-up notifications and the extension's dashboard located in the Chrome menu. The Behaviour Change Wheel theoretical framework [28] was used to guide the development of this tool.

The developed virtual learning assistant works in two main ways. First, the assistant has been designed to conform to the cyclical processes that underlie self-regulated learning [29] by enabling learners to survey their time resources, set goals, monitor progress made towards their goals, and to adjust their initial goals based on received feedback. These actions can all be performed by the learner by using the web interface, which includes learning analytics. Trace data obtained within the extension generates analytics expressed in time spent on-task in online learning environments, web resources used by the learner, and the amount of time spent on off-task activities. Besides the web interface, progress made towards set goals is presented to the learner in their browser dashboard, which is illustrated in Fig. 1.

The second component of the virtual assistant is a series of pop up notifications, which are intended to offer interactions with the learner. The notifications appear on the learner's screen with conditional statements, noting that, for instance, the learner should spend more than a certain amount of time on a given page; that the learner is not using full-screen mode; that the user's cursor is active (a notification will not be sent if the touchpad or the PC mouse are not in use); that the current domain name has not been added by the learner to a list of

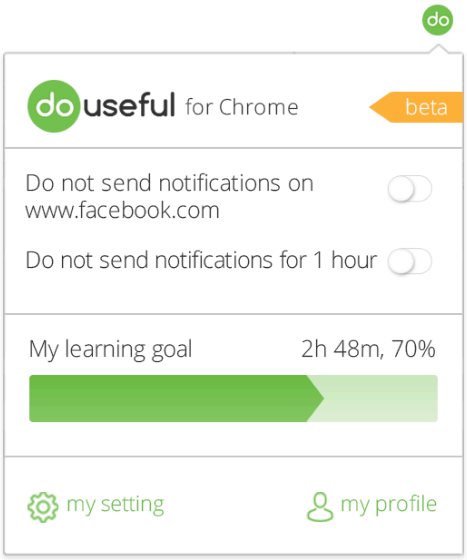

Fig. 1. An example of the drop-down dashboard from the Chrome menu.

websites used to spend time productively. These messages are individualised and may include the learner's name, course name, or the time spent on a current website, and each message is presented at a different time for each participant. The choice of content in each pop-up message is random and based on predesigned templates. An example of the pop-up notification is illustrated in Fig. 2. This kind of external feedback on behaviour should work to draw the learner's attention to any self-regulation problems they might experience. Thus it is hoped that this second component should help learners persist in their online courses.

IV. Conclusion

This paper provides an example of a tool for automated support of SRL skills development, implemented as a virtual learning assistant. Specifically, we introduced the tool's architecture, data collection process, and presented automated interventions designed, aimed at improving SRL skills. The need and potential pathway for further investigation of the possibility to develop and compensate SRL using a virtual assistant and interventions was indicated. In addition, methodological advances expressed in novel data analysis techniques and frameworks such as Multiphase optimization strategy [30], Micro-randomised trials [31], and Just-in-time adaptive interventions [32] may provide useful guidance for the intervention design lead to the development of optimised adaptive interventions in education [33].

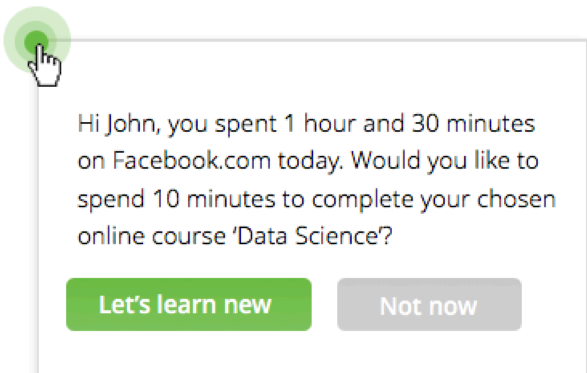

Fig. 2. An example of the notification message.

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