Computers and Education: Artificial Intelligence 4 (2023) 100111

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.sciencedirect.com/journal/computers-and-education-artificial-intelligence

From procrastination to engagement? An experimental exploration of the effects of an adaptive virtual assistant on self-regulation in online learning

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ARTICLE INFO

Keywords:
MOOC
Self-regulated learning
Developmental vs compensatory shifts
Self ratings
Personality
Behavior traces

ABSTRACT

Compared to traditional classroom learning, success in online learning tends to depend more on the learner's skill to self-regulate. Self-regulation is a complex meta-cognitive skill set that can be acquired. This study explores the effectiveness of a virtual learning assistant in terms of (a) developmental, (b) general compensatory, and (c) differential compensatory effects on learners' self-regulatory skills in a sample of $N = 157$ online learners using an experimental intervention-control group design. Methods employed include behavioural trace data as well as self-reporting measures. Participants provided demographic information and responded to a 24-item self-regulation questionnaire and a 20-item personality trait questionnaire. Results indicate that the adaptive assistance did not lead to substantial developmental shifts as captured in learners' perceived levels of self-regulation. However, various patterns of behavioural changes emerged in response to the intervention. This suggests that the virtual learning assistant has the potential to help online learners effectively compensate for deficits (in contrast to developmental shifts) in self-regulatory skills that might not yet have been developed.

1. Introduction

Online learning is an important aspect of contemporary life. The increasing popularity of delivering educational resources in online environments has made educational opportunities more economical and more widely available (Chirikov et al., 2020; Crow, 2013). For educational, personal, and occupational development, it is essential that learners are able to utilise learning opportunities which are increasingly offered online. However, low completion rates, often due to a lack of support (Reich & Ruipérez-Valiente, 2019; Xu et al., 2018), are a common problem for many online learning environments. To help learners to maintain engagement with digital educational content, such as online training or courses, learners need to utilise their self-regulatory skills. Self-regulation plays a key role in online learning environments, and, crucially, is a skill that can be acquired (Schunk & Greene, 2018).

Along with the increasing availability of automated assessment tools (Mojarad et al., 2018; Vytasek et al., 2020; Swiecki et al., 2022; D'Mello et al., 2022; Winne, 2019), several intervention options that utilise state-of-the-art advances in Educational Data Mining (EDM), Leaning Analytics, and Artificial Intelligence in Education (AIED) have been proposed to support online learners' self-regulatory skills. These include standalone systems such as OnTask learning, a platform that provides feedback through personalised messages (Pardo et al., 2018, 2019), or mobile apps such as MyLearningMentor, designed to provide massive open online course (MOOC) learners with personalised planning instruments (Alario-Hoyos et al., 2015). Further examples include Learn-Tracker which records learning time and provides mobile notifications to foster learners' reflective practices (Tabuenca et al., 2015); or virtual companions, such as the one proposed by Sambe et al. (2018), which was designed to provide metacognitive prompts and visualisations of learning indicators. Hybrid systems combine artificial intelligence (AI) and human intelligence to support learners in the transition from AI-regulation to self-regulation, e.g., the system described by Molenaar (2022). Widgets such as the Learning Tracker widget integrate with online courses to support self-regulated learning (SRL) by providing goal-oriented feedback and to encouraging learners' self-reflection (Davis et al., 2016). Virtual learning environments, such as Meta-Tutor, create a virtual learning environment that is designed to detect, track, model, and foster learners' self-regulation with the focus on providing learners with help setting goals (Azevedo et al., 2010) and helping them to self-monitor and utilise SRL strategies (Bouchet et al., 2013; Lallé et al., 2017). Other approaches include extensions to web browsers for which nStudy is an example. It is equipped with the function of assembling web pages based on the learning analytics of learners'

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https://doi.org/10.1016/j.caeai.2022.100111
Received 17 March 2022; Received in revised form 18 November 2022; Accepted 25 November 2022
Available online 12 December 2022
2666-920X/

behaviour (Winne et al., 2017; Winne & Hadwin, 2013). A further example, NoteMyProgress, allows learners to organise their notes, monitor activity on their learning platform, and track time spent on learning activities within and outside a learning platform during a study session (Pérez-Álvarez et al., 2017).

However, effectively scaling SRL interventions remains a challenge, and the effectiveness of interventions depends substantially on their adaptability (Kizilcec et al., 2020). Adaptive assistance is applied in intervention designs in both educational and broad social sciences settings. Adaptive scaffolding has been used effectively to foster self-regulation (e.g., Azevedo et al., 2005; Duffy & Azevedo, 2015) and to enhance learning (e.g., Poitras & Lajoie, 2014). Furthermore, a variety of forms of adaptive assistance with the application of artificial intelligence to support decision-making (Menictas et al., 2019) and predicting outcomes (Mac Aonghusa & Michie, 2021) have become increasingly common in medical research and mobile health applications, known as "just-in-time adaptive interventions" (Nahum-Shani et al., 2018).

To address the problem of an under-utilisation of opportunities offered by online learning, a virtual learning assistant is utilised in this study as an assessment and intervention tool to help online learners to remain engaged with their learning environments. The main assumptions are (a) self-regulation can be developed or learned (Bandura, 1991; Müller & Seufert, 2018; Usher & Schunk, 2018; Zimmerman, 2013), (b) tendencies for procrastinatory behaviour can be identified via behaviour patterns based on trace data (Hadwin et al., 2007; Kizilcec et al., 2017; Maldonado-Mahauad et al., 2018), and (c) failures of self-regulation can be compensated for — at least on a behavioural level — by using an adaptive assistance tool, which was designed to help learners to continue to participate in their online course (Pogorskiy & Beckmann, 2022). In our study, theoretical and practical advances into the research on SRL (Panadero, 2017; Panadero et al., 2017; Winne, 2017) and behaviour change (Michie et al., 2013, 2014) are brought into play, informing the intervention design and the selection of intervention components in order to guide the intervention development and its practical realisation. To conceptualise the aforementioned assumptions, we refer to the Person – Task – Situation (PTS) framework (Beckmann, 2010; Beckmann & Goode, 2017). This perspective allows the effects of the intervention to be evaluated in the three-dimensional space of Person, Task and Situation, where "Situation" is defined as the environment in which a learner performs a given learning task. "Task" is considered as the combination of the learning problem and instructions given to solve the problem. The "Person" dimension in this framework is characterised as the complex of individual differences in cognitive, meta-cognitive, and non-intellective variables.

2. Self-regulation in learning

Self-regulation is defined, in broad terms, as a contextualised and dynamic process used by individuals in an attempt to purposefully initiate, manage and adapt their pursuit of set goals (Cleary & Callan, 2018, p. 338). It plays an important role in determining success for online learners. There are several prominent models of SRL, which are concerned with learners' achievement, behaviour, and utilisation of strategies to pursue desired learning goals. Influential and established models include those proposed by Zimmerman (2000), Boekaerts (1999; 2017), Butler and Winne (1995), Winne and Hadwin (1998), Pintrich (Pintrich & De Groot, 1990; Pintrich et al., 2000), Efklides (2011), and Hadwin et al. (2011). SRL models have evolved over time, with creators significantly modifying many early models to keep up with a changing online landscape. The consensus amongst the literature is that self-regulation in online learning is a skill that can be developed, compensated for, and observed (Pogorskiy et al., 2018). Behaviour, in turn, is the result of internal processes, including affective, cognitive, metacognitive, and motivational components of self-regulation during cyclical sequential phases: planning, monitoring and self-control, and self-evaluation.

2.1. Measurements of self-regulation in online learning

To assess self-regulation in online learning environments, a range of approaches have been applied, including SRL inventories (i.e., questionnaires) (Kizilcec et al., 2017), interviews (Min & Foon, 2019), think-aloud protocols and unstructured interviews (Greene & Azevedo, 2010), clickstream data (Min & Jingyan, 2017), microanalytic methods (Cleary & Callan, 2018), and data mining methods (Biswas et al., 2018) applied to traces of behaviour (Azevedo et al., 2018), including navigation patterns (Jeske et al., 2014). The range of approaches listed above can be classified as self-report or behavioural measures. Each approach can be utilised to assess learners' self-regulatory skills and can be characterised by its level of detail: macro and micro levels (for self-report data) or levels of granularity (for behavioural traces).

Data related to learners' self-regulation can be gathered using self-reporting (e.g., questionnaires) and digital behaviour traces (or simply traces). Utilising behaviour measures to assess SRL allows for timely feedback in response to learners' individual behaviour (Bernacki, 2018; Bernacki et al., 2020). Behaviour traces are predominantly based on clickstream data, that can include learners' interactions with their respective learning management system, pathways through their online course, and data related to learners' social interactions with other learners. The decision over which data to subject to analysis is often pragmatically driven by data availability. Course instructors, for instance, usually have access to data generated within the boundaries of learning management systems in which their course is provided. Whilst such "convenience" might be conducive to a broad, exploratory, primarily-data driven approach, it is limited when it comes to adopting a more conceptually informed approach that focuses on the role of self-regulation.

Research that handles data beyond MOOC environments has started to emerge. For example, Chen et al. (2016) have claimed the first explanatory study to use data beyond MOOC platforms (p. 15). The study analysed user-profiles and activities on StackExchange, GitHub, Twitter and LinkedIn, examining 320,000 learners enrolled on 18 MOOCs. Pérez-Sanagustín et al.'s exploratory study (2019) extended the data scope even further by including learners' interactions with a broader range of web resources, such as social media, news, and search engines. Based on data from 572 learners from four MOOCs, the authors found that additional data can contribute to the prediction of learners' grades on their online courses.

We argue that self-regulation in online learning plays an important role in successfully manoeuvring within the respective learning management systems. SRL might even be of greater importance in the interactions with the various resources outside of the structured environment of learning management systems. Therefore, behaviour traces from learners' interactions with their web environments as a whole is considered informative of learners' SRL. This view resonates with multimodal learning analytics utilised in offline settings, where video recordings and sensors are used as additional data sources (e.g., Järvelä et al., 2020, 2021).

2.2. Development and compensation of self-regulation

Several attempts have been made to design intervention options that foster the development of online learners' self-regulatory skills. A number of systematic reviews report recent advances in research devoted to measuring and supporting learners' self-regulation in online learning environments (Araka et al., 2020; Pérez-Álvarez et al., 2018; Viberg et al., 2020; Wong et al., 2019), including one meta-analysis that focuses on the impact of SRL scaffolds on academic performance in computer-based learning environments (Zheng, 2016). Despite the differences in the approaches taken in these reviews, a core similarity can be seen in the pursuance of the principle to support learners' self-regulation by providing assistance in goal setting, feedback processing, and in self-evaluation, or monitoring. The main focus of generic (i.e., subject-domain unspecific) support in online learning aims to help learners develop self-regulatory skills. Skill development, however, is a complex, dynamic, and non-linear process that is likely to extend over a long period of time. The effects of such developmental processes may therefore not be observable in the short term (e.g., during a particular online course). Therefore, we argue that an apparent lack of measurable effects (e.g., via SRL questionnaires) does not necessarily constitute evidence for the ineffectiveness of the support offered. Adopting a perspective that suits the complex and longer-term nature of skill development, we suggest that the early effects of development should be identifiable in behaviour changes. Such behaviour changes can be interpreted as the initial compensatory steps towards the development of the desired levels in the targeted skill set. In short, interventions provide compensatory strategies that, when utilised by learners, lead to experiences that positively affect the trajectories of skill development (e.g., via habit formation).

2.3. Research questions

The main research question to be examined in the present study is whether online learners' self-regulatory skills can be developed and/or compensated for by providing adaptive assistance. It is assumed that developmental and compensatory shifts in learners result in behaviour change, and that this can be operationalised by analysing behavioural traces. We also assume that developmental and compensatory shifts in learners' self-regulatory skills are determined by learners' individual differences in meta-cognitive and non-intellective variables.

The questions to be addressed are as follows:

RQ1. Can the development of self-regulatory skills in learners be facilitated by adaptive online learning assistance?

RQ2. Can a lack of self-regulatory skills in learners be compensated for by providing adaptive online learning assistance?

RQ3. What is the role of individual differences in the development of compensatory or developmental shifts in self-regulation of learning?

The aim of the present study is to evaluate the compensatory and developmental effects on online learners' self-regulatory skills via an adaptive assistance intervention delivered in the web browser environment.

3. Methods

3.1. Participants

The participants in this study were recruited from a group of online learners who installed the virtual assistant's extension to their web-browser, created an account, logged in to the assistant's website, and indicated that they were attempting to complete an online course that lasted for at least four weeks. The recruitment process comprised multiple pathways. First, the virtual assistant was listed in the Chrome and Firefox web stores, alongside a description and screenshots of the tool. Second, online learners were invited to participate in the study via social media. For instance, a description of the assistant was posted on Facebook groups relevant to popular MOOCs and course platforms. In addition, the study was advertised on the social media website facebook.com, targeting existing users of major learning platforms, such as EdX, Coursera, and Futurelearn. Third, an invitation to participate in the study was posted in connection to two MOOCs offered on coursera.org ("Psychodiagnostics and Psychological Assessment", and "Genius. Talent. Golden Mediocrity"). A page dedicated to the learning assistant was provided on both courses, and an email with a brief description about the tool was sent to those who enrolled in these courses. Finally, a website dedicated to the tool was published. This consisted of a promo page with relevant information regarding the tool which was indexed by search engines, generating additional traffic.

During the data collection period lasting from May to December 2019, 4,329 unique users visited the project website, predominantly from the United States, Pakistan, India, Bangladesh, Russia, France, the United Kingdom, Brazil, Canada, and Australia (these are the top ten countries based on the number of unique visitors to the project website). The flow diagram presented in Fig. 1 illustrates the progression of registered users ($N = 344$) through the key steps of the main study: from creating an account on the project website to the assessment of eligibility, randomisation to experimental conditions, progression to pre- and post-intervention assessments. As can be seen in Fig. 1, some users were not included in the study. This was either due to users not meeting the inclusion criteria or because they were unwilling to provide informed consent to participate. The inclusion criteria were as follows: adult learners (18 years of age or over) who attempted to complete an online course that lasted at least four weeks since being enrolled in the study. After screening, of those online learners who expressed interest in using the learning assistant (335 users), 178 did not meet these criteria, including 66 learners who decided to withhold their informed consent to participate and therefore were not included in the study. Also, this flow diagram shows a marked attrition rate for enrolled participants in responding to post-intervention measures (there was only one occasion of measuring the response at the end of the experimental period; please note, post-intervention and follow-up are used interchangeably).

Participants ($N = 157$) were predominantly male (70%) with an average age of just below 27 years ($M = 26.68$, $SD = 7.36$). More than half of the participants had completed at least an undergraduate degree (52.9%) and had some experience in online learning (only 13.4% of the participants indicated that they had no experience in online learning). However, not all study participants provided their demographic information. The demographic questionnaire was voluntary, and some participants opted not to provide their demographic information by skipping some of the respective questions in the survey. The enrolment rate of all registered users stood at 45.6% after assessing participants' eligibility and securing their informed consent. Participants' willingness to complete the post-intervention questionnaire was about a third (33.1%) of all enrolled, or 15.1% of all registered users. The observed low response rate is consistent with previously reported high participant attrition rates typical of longitudinal educational and medical studies using tracking devices or a voluntary post-intervention questionnaires in studies focusing on MOOCs (e.g., Jansen et al., 2020; Kramer et al., 2019).

Participants were from 39 different countries. Countries with more than one participant are shown in Table 1. In addition, there was one participant from each of the following countries: Australia, Bahrain, Cameroon, Chile, Cyprus, France, Greece, Hong Kong, Italy, Jordan, Korea, Morocco, Myanmar, Nepal, New Zealand, Nigeria, Peru, Poland, Serbia, Switzerland, Syria, Uganda, and Ukraine.

It has been shown in previous studies that the MOOC population tends to be predominantly male; the typical ratio is 2:1 in favour of male learners (Glass et al., 2016, p. 43). However, gender ratio varies across different course subjects, but also, to some extent, across different course platforms and geographical regions. For example, in a large survey of MOOC participants, the proportion of female learners was 29%, as reported in responses collected from 597,692 learners enrolled in 17 courses offered by HarvardX and MITx on the edX platform (Ho et al., 2014, p. 2). Another survey of 34,779 MOOC participants based on the University of Pennsylvania's 32 MOOCs offered on the Coursera platform showed that the proportion of learners identifying as female stood at 41.3% for the United States, but at only 31.1% of learners from BRICS (Brazil, Russia, India, China, and South Africa) (Christensen et al., 2013, p. 10).

In the sample for the current study, the proportion of participants who indicated their gender as "female" was 13.4%. It should be noted that a relatively high proportion of participants (14.6%) did not provide information regarding their gender. Whilst MOOC participants' median age has usually been 30 or younger, the proportion of learners aged 30

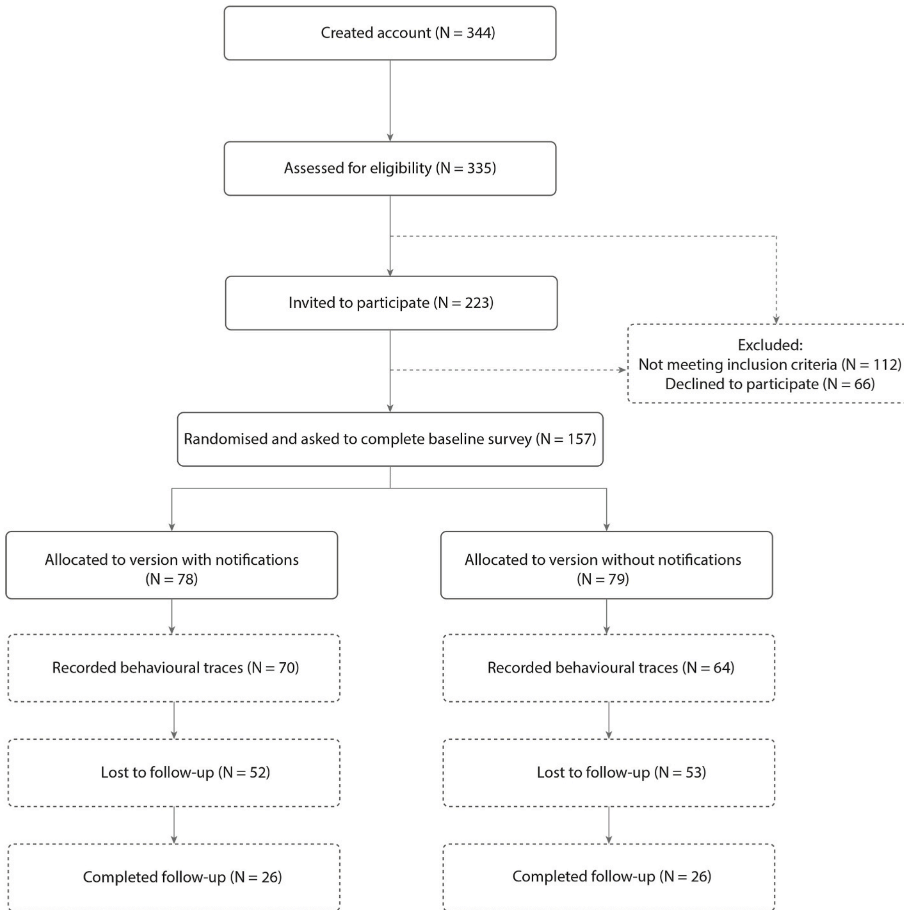


Fig. 1. Flow diagram of participants' enrolment, allocation to experimental conditions, and data collection.

Table 1
Countries of origin indicated by participants.

Country	*N*	Country	*N*	Country	*N*	Country	*N*
Bangladesh	37	Brazil	3	Sri Lanka	3	Germany	2
Pakistan	27	Colombia	3	Vietnam	3	Kenya	2
India	24	Ecuador	3	Canada	2	Portugal	2
United States	4	South Africa	3	Egypt	2	Russia	2

and older enrolling in online courses tends grow (Glass et al., 2016, p. 42). As the field of online learning matures, the age range of participants is generally widening as more school students and established professionals participate in MOOC learning. For example, MOOC learners' level of education used to be dominated by participants with college degrees (Glass et al., 2016, pp. 41–55; Liyanagunawardena et al., 2015). As MOOCs become a more widely accepted and utilised mode of delivering educational programs and as an opportunity for self-study, more people have started to enrol in MOOCs, resulting in more participants with prior experience using MOOCs. For example, an analysis of responses collected from 4,503 participants enrolled in 17 courses on the Coursera platform revealed that learners with no previous experience in MOOCs account for 16.3% of all responses, learners who previously tried up to 5 courses accounted for 47.8%, from 5 to 10 courses — 22.4%, and learners with more than 10 courses in their background consisted of 13.5% of all responses (Li, 2019, p. 21). In this regard, it is reasonable to claim that the composition of the sample of participants in the current study mirrors the general MOOC learner population in terms of age, gender, educational level, and online learning experience.

3.2. Intervention

The virtual assistant, used as an intervention tool in this study, was implemented in the form of an application as an extension to the Chrome and Firefox web browsers. It comprises a web interface with learning analytics and tools to adjust personal settings, and a database for collected trace data. The decision to use the above-mentioned web browsers was determined by their popularity: nearly 80% of all internet desktop users used either Chrome or Firefox as their web browser at the time of the data collection period (Netmarketshare, 2020).

The virtual assistant was developed in 2017, and the first explorative study utilising the tool was conducted on a limited number of online learners in 2018. In our earlier publication (Pogorskiy & Beckmann, 2022), we demonstrated the main functionalities and algorithmic base utilised in the virtual assistant by presenting a detailed examination of a single learner's web navigation behaviour over a nearly one-year period. For the purposes of this study, and based on the results of a pilot study, we refined the virtual assistant to better facilitate and accommodate the collection of self-report measures, in addition to trace data and distributing assistance across the learning cycle.

The assistant provided a generic intervention component and an adaptive intervention component comprising a wide range of individualised pop-up notifications. The generic intervention component included modules which aimed to support the different stages of SRL, including planning and goal setting, self-monitoring, and self-evaluation. This component included the following modules: (1) A goal setting module, used to indicate an online course a participant intends to complete, alongside the required time-frame. Fig. 2 illustrates the goal setting interface where learners can indicate online courses they intend to complete. (2) Dashboards with learning analytics, illustrating

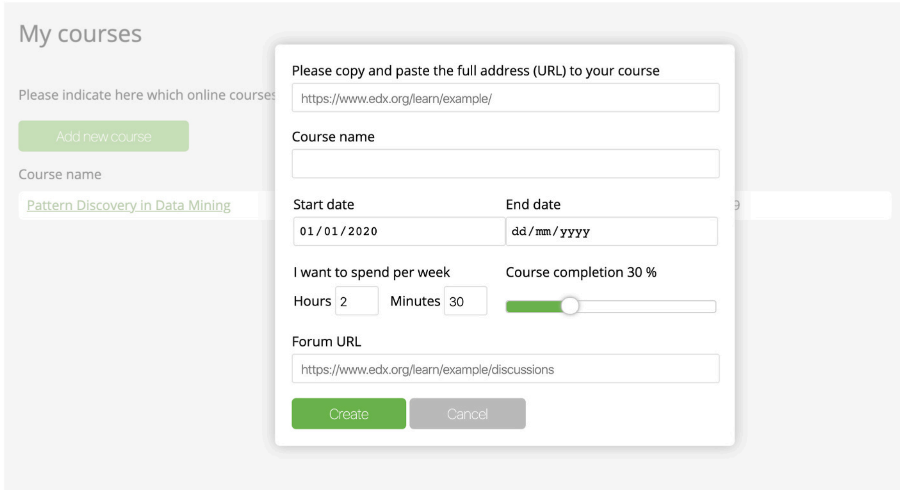


Fig. 2. Example of the user interface to support the goal setting and goal adjustment functionality of the tool.

the time spent online using the different web resources. Fig. 3 illustrates an example of the user interface where a learner can access their recorded behaviour (behaviour recorded with the web browser extension of the tool). (3) Dashboards with learning analytics illustrating time spent towards indicated goals. Fig. 4 illustrates an example of the dashboard with summary statistics of time contributed by a learner to their selected course.

The adaptive assistance intervention component consisted of a pool of pre-designed message templates and a module with personalised settings to adjust the appearance of the messages. The pre-designed message templates are activated depending on an individual learner's browsing behaviour and settings adjusted by a learner for their web browser environment. The activation of each of these tailored messages was based on a set of pre-specified decision rules considering learners' individualised profile settings and their performed actions (e.g., online behaviour) using the Behaviour Change Wheel framework (Michie et al., 2014). The content of these notification templates was informed by theories of SRL and the Behaviour Change Technique taxonomy (Michie et al., 2013).

Fig. 5 illustrates an example of the pop-up messages that would appear in a learner's web-browser environment, in response to online behaviour. Based on the SRL theoretical framework, the pre-specified decision rules were selected based on apparent lapses of SRL. Therefore, their occurrence signals the need for self-regulatory assistance. As can be seen from Fig. 5, a message appeared on a learner's screen accompanied by two buttons. A click on either button determined the learner's response to the message — dismissal (click on the “Not now” button) or acceptance (click on the “Let's learn new” button). In case of acceptance, the learner was redirected to their course webpage. Learners' responses to such messages were then saved in the tool's database.

The task of regulating the intensity of assistance is partly shared with a learner by allowing personalisation of decisions regarding when the assistance occurs. Figs. 6 and 7 illustrate dashboards where learners can indicate time settings and create lists of websites that are considered in the decision rules.

3.3. Design

The main aim of this study was to evaluate the effects of the adaptive assistance on learners' self-regulation in terms of SRL developmental and/or compensation for SRL deficits. The study, therefore, included a set of behavioural and self-report measures. Participants who were randomly allocated to the control condition received the generic intervention component. Participants in the intervention condition received additional adaptive interventions in the form of pop-up messages on screen. These included two main types of personalised notifications: (a) triggered when procrastinatory behaviour was detected, and (b) triggered after 25 min of engagement with their selected online courses. The former type aimed to direct learners towards practising self-regulation, the latter type aimed to encourage a continuation of the engagement with the learning session. The rationale for providing participants in the control group with the generic intervention component was to mitigate the risk of dropout in the control group; it was expected that participants would find the presence of at least some basic functionality beneficial, prompting them to continue using the tool.

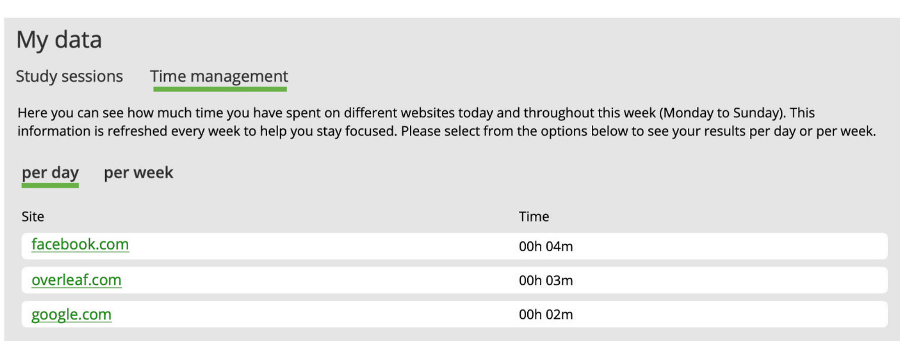


Fig. 3. Example of the user interface to support the self-monitoring of behaviour functionality of the tool.

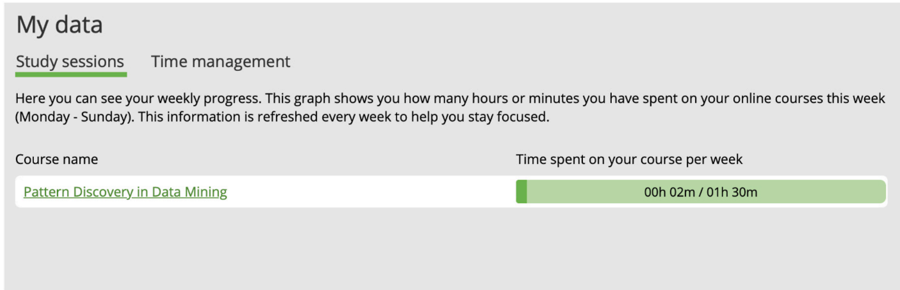


Fig. 4. Example of the user interface to support the self-evaluation functionality of the tool.

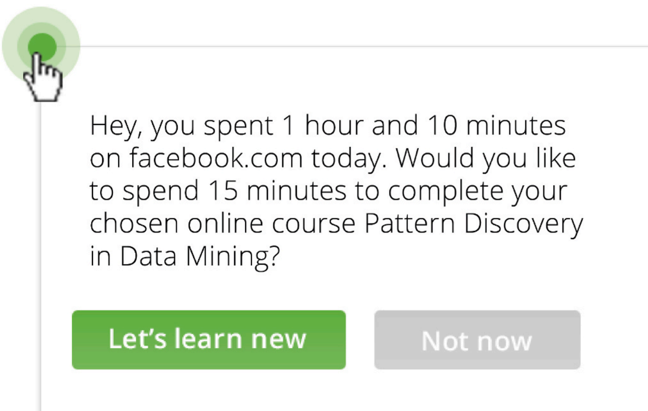


Fig. 5. Example of the pop-up notification functionality of the tool.

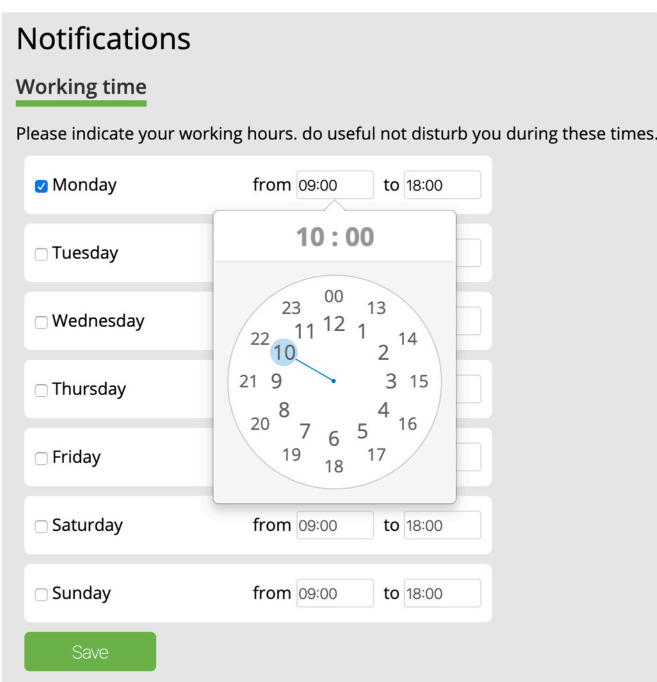


Fig. 6. Example of the dashboard to indicate time settings when the appearance of the pop-up notifications is limited.

3.4. Measures

3.4.1. Baseline

Prior to being exposed to the intervention, participants were asked to provide some basic demographic information (age, gender, geographical location by country, educational attainment, and prior online learning experience). Participants' level of SRL skills was measured using a questionnaire proposed by Barnard et al. (2009) which builds on a 86-item questionnaire proposed by Zimmerman (1998) (see also Barnard-Brak et al., 2010, p. 65). This questionnaire is widely utilised in research on online and blended learning environments (e.g., Li, 2019; Li et al., 2020; Papamitsiou & Economides, 2019; Vanslambrouck et al., 2019) and has been translated, validated, and applied in different languages (e.g., in Russian (Martinez-Lopez et al., 2017) and Chinese (Fung et al., 2018)).

The questionnaire used in the present study comprises 24 questions that cover six sub-dimensions of SRL. These dimensions include: Goal Setting (for example, "I set goals to help me manage studying time for my online courses" statement item), Environmental Structuring (e.g., "I choose a time with few distractions for studying for my online courses"), Task Strategies (e.g., "I work extra problems in my online courses in addition to the assigned ones to master the course content"), Time Management (e.g., "I try to schedule the same time everyday or every week to study for my online courses, and I observe the schedule"), Help Seeking (e.g., "I am persistent in getting help from the instructor through e-mail"), and Self Evaluation (e.g., "I summarize my learning in online courses to examine my understanding of what I have learned"). Separate scores for each of the six sub-scales, as well as an overall SRL score, were derived using a 5-point Likert-type response format ranging from "Strongly disagree" (1) to "Strongly agree" (5). Responses were scored in such a way that higher scores would indicate higher levels of self-regulatory skills.

In addition, as a marker of non-intellective individual differences relevant to learning and self-regulation the 20-item International Personality Item Pool questionnaire (IPIP, Donnellan et al., 2006; Goldberg et al., 2006) with a 5-point Likert-type response format was administered. The IPIP questionnaire is based on the Five Factor Model of personality (FFM, Costa & McCrae, 1992). It assesses five broad-level personality dimensions (openness, conscientiousness, extraversion, agreeableness, neuroticism) and results in a description of an individual's personality, i.e., their thoughts, feelings, and behaviour, in terms of their positioning on each of these five major personality dimensions or traits. According to McCrae and Costa (1987), the core of *Extraversion* is lively sociability, the enjoyment of being accompanied by others. Other researchers (e.g., Hogan, 1982) state that this dimension should be understood in terms of sociability and assertiveness factors. *Agreeableness* refers to being cognitively trustful, affectively sympathetic, and behaviourally cooperative (McCrae & Costa, 1987). *Conscientiousness* has "both proactive and inhibitive aspects", including traits such as "need for achievement and commitment to work", and "moral scrupulousness and cautiousness" (Costa et al., 1991, p. 887). *Neuroticism* includes "not only negative affect, but also the disturbed thoughts and behaviours that accompany emotional distress" (McCrae & Costa, 1987, p. 87). *Openness* "is best characterised by original, imaginative, broad interests, and daring" (McCrae & Costa, 1987, p. 87). For the present study, participants' responses to each subscale were averaged to

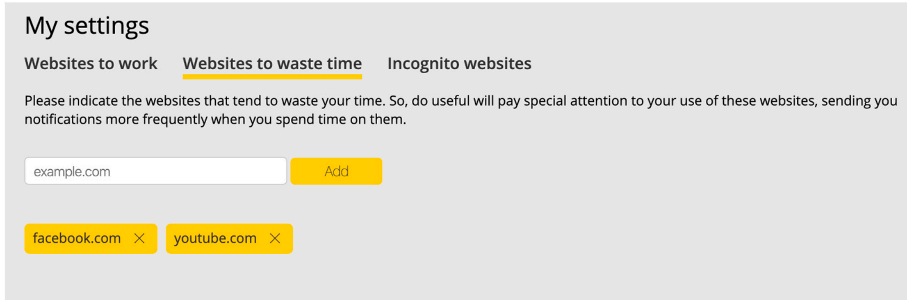


Fig. 7. Example of the dashboards to classify URLs: non-productive websites.

obtain an indicative score for each subscale. In the case of the SRL questionnaire, a mean value of these six averaged sub-scales was calculated to obtain the SRL total score.

3.4.2. Behavioural measures

Learners' trace data were logged for each online session they engaged in. Trace data comprised the domains visited (e.g., "facebook. com", "instagram.com", "news.mit.edu" without detailing the full URL), a timestamp of the visit and time spent on each domain. Behavioural data also included participants' responses to notifications that were provided in the form of on-screen pop-up messages. The registered responses reflect the acceptance or rejection of the given pop-up message linked with the date and time of the receipt of the message. In addition, learners were able to provide general information regarding their online courses (course name, start and end dates), create their own lists of websites categorised as "entertainment", "websites to work", and "incognito websites". This information enabled further individualisation of the adaptive assistance provided by the online tool.

The collected dataset of participants' web navigation and interactions with their web browser environments (trace data) consisted of 443,131 records from across 134 participants, 70 of which have been allocated to the intervention condition. In order to examine and compare participants' behaviour trace data on an aggregated level, several data transformation steps were taken. As data collection for this study took place over several months and participants started and finished their online learning course at different dates, time series data were standardised for comparability between participants on the same time scale (i.e., days in the study: from day one to day 28). The web navigation behaviour trace data collected during the study period consisted of 17,064 unique URL records. Some, however, represented similar online resources, such as "google.com" and "google.co.uk". To overcome the issue of unnecessarily treating these as qualitatively different, and to allow comparisons across participants in terms of visited URLs, unique URLs were grouped into six major categories: "youtube", "social media", "productivity", "education", "entertainment", and "other". In addition to websites that are commonly classified as educational URLs such as ide.cs50.io for the course "CS50's Introduction to Computer Science" on the platform edx.org, web addresses were added so that participants were able to identify that these were directly related to their online courses (e.g., edx.org, coursera.org, w3schools.com). Frequently mentioned websites with known affiliations to educational institutions, such as domains located in the hosted zones ".ac.uk", ".ac.nz", ".edu.au", and ".edu", were also included in the category of educational URLs. The most frequently appearing 273 unique URLs were manually coded (1.6% of all unique URLs), resulting in 291,500 records being categorised from the total 443,131 (65.8% of all records). This categorisation accounted for 78.2% of all participants' recorded time spent online. It is worth acknowledging that (a) classifying web domains such as Social Media or YouTube are not clear cut as some visits to these websites might serve serve as procrastinatory behaviour, whilst other visits are made with an educational focus, and (b) as is the case with all categorisation attempts, there is the risk of oversimplifying the complexity of a learner's behaviour. However, this trade-off is necessary in order to examine (groups of) individual learners' behaviour across different web resources visited within a certain time window, and then to compare these data.

3.4.3. Outcome measures

To operationalise change in (self-reported) self-regulation, participants were asked to respond to the Online Self-Regulated Learning Questionnaire (OSLQ, Barnard et al., 2009) again after a four-week period. Changes in participants' self-regulation scores served as indicators for potential *developmental* effects. Changes in online behaviour throughout the course, with a particular focus on time dedicated to educational URLs, and the ratio between time spent on web resources categorised as educational and the total time spent online, were considered indications of *compensatory* effects. In addition to these primary outcomes, behaviour data reflecting changes in time spent on other categories of web resources (e.g., entertainment and social media) are considered secondary outcomes that capture time-varying effects of the adaptive assistance.

3.5. Procedure

Participants who (a) have created an account on the website set up for the online learning assistant, (b) installed the extension to their web browser, and (c) met the inclusion criteria were asked to provide informed consent for participating in this study. Participants were then automatically randomised into one of two experimental conditions. For the intervention group, the online learning assistant provided individualised in-browser notifications in addition to information provided on their respective account dashboard. Whilst this information was also available for learners allocated to the control condition, the feature of individualised and adaptive notifications was disabled.

Following the registration and allocation process, participants provided demographic information and responded to a 24-item self-regulation questionnaire and a 20-item personality trait questionnaire. The application then began collecting trace data for each participant's activity in relation to their web navigation behaviour. Users who did not meet the inclusion criteria or who were not willing to provide informed consent were not included in the study (no self-report and trace data were collected) but were given access to the version of the tool with the adaptive assistance in their web browser environment. The total duration of the study for each participant was 30 days. No reward or remuneration for participation was provided. Behavioural trace data were collected during a four-week period. 30 days after each participant's enrolment, the online SRLQ was re-administered to all participants. All collected data were anonymised at point of recording and used solely for research purposes.

3.6. Data analysis

In the primary analysis, the effect of the adaptive assistance on either developing or compensating self-regulation was evaluated by

Table 2
Descriptive statistics for study variables before and after attrition across experimental conditions.

	Baseline			Baseline (for those who provided follow-up)		
	All	Control	Intervention	All	Control	Intervention
N	157	79	78	52	26	26
Age (*M* (*SD*))	26.68 (7.36)	26.28 (7.54)	27.13 (7.19)	27.55 (8.94)	27.21 (10.52)	27.88 (7.32)
Gender (%)						
Not provided	23 (14.6)	8 (10.1)	15 (19.2)	8 (15.4)	4 (15.4)	4 (15.4)
Female	21 (13.4)	13 (16.5)	8 (10.3)	7 (13.5)	3 (11.5)	4 (15.4)
Male	110 (70.1)	57 (72.2)	53 (67.9)	35 (67.3)	18 (69.2)	17 (65.4)
Other	3 (1.9)	1 (1.3)	2 (2.6)	2 (3.8)	1 (3.8)	1 (3.8)
Education (%)						
Not provided	11 (7.0)	2 (2.5)	9 (11.5)	1 (1.9)	1 (3.8)	0 (0.0)
Doctorate	2 (1.3)	0 (0.0)	2 (2.6)	1 (1.9)	0 (0.0)	1 (3.8)
Other education	5 (3.2)	2 (2.5)	3 (3.8)	1 (1.9)	1 (3.8)	0 (0.0)
Postgraduate	37 (23.6)	21 (26.6)	16 (20.5)	15 (28.8)	7 (26.9)	8 (30.8)
Primary school	1 (0.6)	1 (1.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
Secondary school	18 (11.5)	8 (10.1)	10 (12.8)	8 (15.4)	4 (15.4)	4 (15.4)
Undergraduate	83 (52.9)	45 (57.0)	38 (48.7)	26 (50.0)	13 (50.0)	13 (50.0)
Experience (%)						
Not provided	20 (12.7)	9 (11.4)	11 (14.1)	2 (3.8)	2 (7.7)	0 (0.0)
Completed at least one course	35 (22.3)	15 (19.0)	20 (25.6)	20 (38.5)	8 (30.8)	12 (46.2)
Completed many online courses	24 (15.3)	14 (17.7)	10 (12.8)	11 (21.2)	6 (23.1)	5 (19.2)
No experience	21 (13.4)	10 (12.7)	11 (14.1)	5 (9.6)	2 (7.7)	3 (11.5)
Tried some courses	57 (36.3)	31 (39.2)	26 (33.3)	14 (26.9)	8 (30.8)	6 (23.1)
Personality traits (*M* (*SD*))						
Neuroticism	3.08 (0.60)	3.01 (0.61)	3.14 (0.58)	3.12 (0.76)	3.05 (0.82)	3.19 (0.71)
Extraversion	2.70 (0.71)	2.65 (0.77)	2.74 (0.64)	2.71 (0.83)	2.56 (0.95)	2.86 (0.67)
Openness	3.44 (0.87)	3.48 (0.89)	3.40 (0.85)	3.76 (0.87)	3.92 (0.82)	3.60 (0.90)
Agreeableness	3.49 (0.76)	3.39 (0.82)	3.59 (0.69)	3.68 (0.72)	3.68 (0.79)	3.68 (0.67)
Conscientiousness	3.11 (0.72)	3.14 (0.73)	3.07 (0.73)	3.14 (0.80)	3.13 (0.84)	3.15 (0.76)
SRL total score (*M* (*SD*))	3.41 (0.91)	3.40 (0.85)	3.43 (0.98)	3.17 (0.80)	3.00 (0.73)	3.35 (0.84)
SRL subscales (*M* (*SD*))						
Goal setting	3.49 (1.05)	3.49 (0.97)	3.49 (1.15)	3.40 (1.01)	3.27 (1.06)	3.53 (0.97)
Environment structuring	3.78 (1.03)	3.83 (0.94)	3.73 (1.11)	3.65 (1.05)	3.50 (1.05)	3.79 (1.04)
Task strategies	3.22 (1.13)	3.13 (1.08)	3.32 (1.19)	2.97 (1.11)	2.56 (0.90)	3.37 (1.16)
Time management	3.24 (1.22)	3.27 (1.18)	3.22 (1.28)	2.90 (1.22)	2.85 (1.22)	2.96 (1.25)
Help seeking	3.21 (1.20)	3.19 (1.18)	3.23 (1.23)	2.83 (1.10)	2.70 (1.11)	2.96 (1.10)
Self evaluation	3.54 (0.99)	3.50 (0.93)	3.57 (1.04)	3.29 (0.87)	3.09 (0.79)	3.49 (0.92)

contrasting outcomes obtained in the intervention and control group. To test for developmental effects analyses of covariance (ANCOVA) for the SRL total score and for each of the six subscale scores as dependent variable and the respective baseline score as covariate were carried out. To assess the potential compensatory effects of the adaptive assistance on main outcomes, we visualised behavioural data collected over the course of participants' online learning. Polynomial regression curves were fitted to examine trends in selected online behaviours. A combination of these approaches was utilised to ascertain the role of individual differences in compensatory and developmental shifts in the self-regulation of learning.

In order to minimise sampling bias in answering the research questions, we first performed randomisation checks to determine whether the missing data occurred at random. In our answer to the first research question, we only analysed participants who completed both the pre- (baseline) and post-intervention measures. In our answer to the second research question, the collected trace data among all participants who provided their behavioural traces were aggregated on an experimental group level. To answer the third research question, we analysed data from participants who responded to the baseline questionnaires and provided their behaviour traces.

To test for developmental effects, SPSS Statistics was utilised. To visualise behaviour traces and examine them for compensatory effects and the role of individual differences in behavioural shifts, we utilised various Python data handling and visualisation packages, including Altair, NumPy, Pandas, Seaborn, and Statsmodels.

4. Results

Table 2 provides an overview of the descriptive statistics of the study variables, including demographic information. Studies of online learning with a longitudinal scope that depend on responding to additional requests for data collection are notoriously plagued by high rates of participant attrition (e.g., Jansen et al., 2020; Kramer et al., 2019). In typical experimental study designs, such as randomised controlled trials, detecting an effect of medium size with sufficient statistical power (with a significance level of 5%, random allocation to experimental groups and a two-tailed test), requires a sample size of 104 participants. The following variables for calculating the minimally required sample size were provided: control $M = 3.32$, control $SD = 0.9$ and expected change in the overall SRL score = 0.5 utilising the "pwrcalc" R package. These assumptions for baseline levels are based on previously reported average levels of participants' SRL scores assessed by the OSLQ using a 5-point Likert-type response format (Fung et al., 2018; Lai & Hwang, 2016; Lin et al., 2016; Martinez-Lopez et al., 2017).

The sample recruited for the present study included $N = 157$ participants that were randomly allocated to the two experimental conditions. However, the problem of participant attrition is a well known constraint to longitudinal research, and our study is no exemption. Participant attrition affects the minimally detectable effect size and to better contextualise the results, we report a post hoc power analysis in Section 4.1. To ensure that we extract the maximum information value from the data that we were able to collect, without running the risk of over-claiming generalisability, we have conducted an attrition analysis first. This includes, in addition to the obligatory randomisation check, tests for general as well as differential attrition effects. The randomisation check relevant to our study entails a comparison of the two experimental groups on measures obtained at baseline.

We expect no systematic group differences between the control and the intervention group. For the purpose of testing for general attrition, we compare baseline data between the subsample of those who provide a complete data set (provide responses to the post-intervention questionnaire) and those who drop-out (i.e., those who do not provide responses to the post-intervention questionnaire). The outcome of such a comparison will indicate whether attrition is at random or (partly) caused by study features. The outcome has implications for the generalisability of the study findings in relation to the sample of online learners who volunteered to participate initially. The test for differential attrition effects checks whether the attrition rate differs between the control and intervention groups. Differential attrition occurs, for instance, if the distribution of learner attributes in the intervention group differs from the distribution in the control group. It would suggest that features of the intervention might have more strongly encouraged some online learners to either continue with or to disengage from the study. Such effects also have implications in terms of the generalisability of effectiveness claims related to the intervention. To test for these effects, we have conducted two-factorial analyses of variance (ANOVA) for the target variable (i.e., SRL) and its subdimensions assessed at baseline, as well for the five personality traits. The main effect related to the group factor (control vs. intervention) is indicative of the randomisation effectiveness. The main effect of the status factor (remain vs. drop-out) is indicative of general attrition. The interaction between these two factors (group by status) represents a test for differential attrition effects.

The results of performing a randomisation check for the target variable, i.e., SRL (total score), presented in Table 3 indicate no systematic differences between the control and intervention group at baseline. This result pattern also holds at the sub-dimensional level for SRL (Goal setting, Environmental structuring, Task strategies, Time management, Help seeking, and Self evaluation). The randomisation check for the non-target variable (i.e., personality trait dimensions) supports the assertion of comparability of intervention and control groups (Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness).

In terms of general attrition effects, the analysis for the target variable presented in Table 4 reveals that online learners with higher levels in SRL were more likely to disengage over the course of the 30-day study period. This effect is mainly due to participants with higher levels in Task strategies, Time management, Help seeking, and Self evaluation, whilst differences in Goal setting and Environmental structuring were negligible.

A randomisation check for explorative analyses of behaviour trace data presented in Table 5 revealed that the intervention group and the control group did not differ on average in terms of their SRL total score, their scores in all of the six SRL sub-scales (Goal setting, Environmental structuring, Task strategies, Time management, Help seeking, and Self evaluation), as well across the five personality dimensions assessed at baseline (Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness). This outcome reveals the importance of comparing behaviour traces between the two experimental groups.

With regard to personality traits as assessed with the IPIP questionnaire, it appears that participants lower in Openness and Agreeableness tend not to provide responses to the post-intervention SRL questionnaire, as presented in Table 6. No general attrition effects were observable in relation to Neuroticism, Extraversion, and Conscientiousness.

These attrition effects did not differ between the control and intervention condition, except for the SRL dimension Task Strategies. Participants with higher levels of self-reported Task Strategies who were allocated to the control condition, where they did not receive tailored support impulses from the online learning assistant, were less likely to follow the invitation to fill in the SRL questionnaire at the end of their 30-day online learning experience.

The nature of general attrition complicates our ability to make generalisations about the overall findings for the population of online learners, however defined. Differential attrition effects draw attention to the features of the intervention (or the absence thereof) that might have an impact on the emergence of potential intervention effects, as such. In the context of the study at hand, the differential attrition effect results in an incomparability of control and intervention group in regard to Task Strategies ($F_{1,133} = 6.487$, $p = .012$, $\eta_p^2 = 0.047$), which has to be taken into account when testing for potential intervention effects.

Table 3
Two-factorial ANOVAs randomisation checks for the target variable and personality traits assessed at baseline.

Variable	$F_{1,133}$	p	η_p^2
SRL total score	0.339	.562	.003
Goal setting	0.066	.797	<.001
Environmental structuring	0.17	.898	<.001
Task strategies	2.636	.107	.019
Time management	0.004	.950	<.001
Help seeking	0.144	.705	.001
Self evaluation	0.678	.412	.005
Personality traits	$F_{1,121}$	p	η_p^2
Neuroticism	1.431	.234	.012
Extraversion	0.811	.37	.007
Openness	0.556	.457	.005
Agreeableness	1.606	.208	.013
Conscientiousness	0.182	.67	.002

Table 4
Two-factorial ANOVAs checks for general attrition effects.

Variable	$F_{1,133}$	p	η_p^2
SRL total score	5.977	.016	.043
Goal setting	0.622	.432	.005
Environmental structuring	1.3	.256	.010
Task strategies	4.43	.037	.032
Time management	6.675	.011	.048
Help seeking	8.584	.004	.061
Self evaluation	5.436	.021	.039

Table 5
Randomisation checks for explorative analyses of behaviour trace data.

Variable	$F_{1,115}$	p	η_p^2
SRL total score	0.121	.729	<.001
Goal setting	0.001	.973	<.001
Environmental structuring	0.061	.806	.001
Task strategies	1.506	.222	.013
Time management	0.017	.896	<.001
Help seeking	0.063	.803	.001
Self evaluation	0.313	.577	.003
Personality traits	$F_{1,105}$	p	η_p^2
Neuroticism	1.959	.165	.018
Extraversion	0.705	.403	.007
Openness	0.371	.544	.004
Agreeableness	2.026	.158	.019
Conscientiousness	0.080	.778	.001

Table 6
Two-factorial ANOVAs checks for explorative analyses of the role of personality traits on participants' willingness to provide responses to the post-intervention SRL questionnaire.

Variable	$F_{1,121}$	p	η_p^2
Neuroticism	0.497	.482	.004
Extraversion	0.019	.889	<.001
Openness	13.782	<.001	.102
Agreeableness	6.145	.015	.048
Conscientiousness	0.238	.627	.002

Research conducted by Greene et al. (2015, pp. 944–945) suggests that online learners with little or no prior experience in online learning on MOOCs are more likely to drop out of their courses. The participant retention observed in this study tends to resonate with this finding. In our study, about 50% of participants reported having either no prior experience in online learning or only having tried some online courses. This percentage falls to less than 37% in the sample of learners who responded to the follow-up (see Table 2).

The difference in the overall level of self-regulation measured at baseline between participants who responded to the follow-up questionnaire and all enrolled participants indicates that learners with higher levels of self-regulation who were allocated to the control group were less likely to provide responses to the post-intervention questionnaire. In previously reported studies (see, for example, Fung et al., 2018; Lai & Hwang, 2016; Lin et al., 2016; Martinez-Lopez et al., 2017) the average level of participants' SRL scores assessed by the OSLQ using the same 5-point Likert-type response format was 3.32, with a standard deviation of 0.9 across all four of their studies. The overall SRL mean score of 3.41 and the standard deviation of 0.91 recorded at baseline with administering the pre-intervention questionnaire for participants from both groups provides the assurance that the study sample does not significantly deviate from the general population of online learners.

4.1. Developmental effects

To evaluate the potential developmental effects of the adaptive assistance (research question 1) and taking the attrition-related result pattern into account, ANCOVAs with the post intervention SRL total score and each of the SRL subscale scores as dependent variable and the respective baseline score as covariate were conducted. The estimates for the average group effects (control vs. intervention) were considered indicative of potential developmental effects of the adaptive online learning assistant. The considerable attrition renders statistical testing for potential developmental effects challenging. Given the remaining sample size, the minimal detectable effect would have to be comparable to $\eta_p^2 > .13$ (equiv. $f > 0.39$, or $d > 0.78$, Cohen, 1988, p. 281) to have a 0.80 probability of being detected. This attrition-reduced sensitivity needs to be taken into account when interpreting the results (see Table 7).

The results presented in Table 7 indicate that being exposed to the adaptive assistance did not result in significantly different developmental trajectories in terms of SRL when compared to the control condition. This result seems mirrored — although to slightly varying degrees — in the analyses on sub-dimensional levels of SRL. However, given the general attrition effects, which resulted in lowered sensitivity overall, and the differential attrition effects, which jeopardised comparability of experimental groups, these results need to be interpreted with caution. A graphical representation of group-specific trajectories as shown in Fig. 8 may serve this purpose.

In conclusion, the results of the analysis in relation to research question 1 suggest that the adaptive assistance provided by the virtual learning assistant did not result in statistically coverable developmental shifts in learners' self-regulation as assessed via conventional self-report measures. An appropriate interpretation of these results needs to take into account that the available sample size only permits us to rule out the existence of *large* effects with sufficient statistical power. Expecting the adaptive assistance to have large effects on self-rated learning behaviour to emerge (a) in a relative short period of time and (b) in comparison to a condition that also receives — albeit not the adaptive assistance, but the generic intervention component in form of a "learner's dashboard", would rather be ambitious.

Table 7
ANCOVA results to test for potential developmental effects.

Variable	$F_{1,49}$	p	η_p^2
SRL total score	0.244	.623	.005
Goal setting	3.947	.053	.075
Environmental structuring	0.360	.551	.007
Task strategies	2.812	.100	.054
Time management	0.019	.892	.001
Help seeking	0.114	.737	.002
Self evaluation	2.450	.124	.048

4.2. Compensatory effects

This section aims to answer the second research question: whether a lack of self-regulatory skills in learners can be compensated for by providing adaptive online learning assistance. To address this research question, we analysed behavioural data collected over the course of the participants' online learning. Whilst focusing on answering research question 2, the analyses conducted are primarily exploratory in nature.

As a result of the preparatory steps described in previous sections, participants' time spent on different categories of URLs was visualised in Fig. 9. In this figure, the time each learner spent online on different website categories is shaded in grey. The darker the shading, the higher the frequency in visits to the respective website categories across participants. Peaks in lighter grey represent individual learners' records for those days. The height of peaks represents the duration of the visits. It is noticeable from the first row of the graph that participants allocated to the intervention group tended to spend more time on educational URLs at the beginning and at the end of their enrolment in the study, with a noticeable dip between day 13 and day 20 (note: two peaks near day 17 symbolise two participants' sessions). Behaviour traces in terms of time spent on URLs categorised as "entertainment" seem to be slightly less variable for participants allocated to the intervention group, whilst participants in the control group showed some extremes in daily session lengths. A similar pattern can be identified for websites falling into the category "other". There are discernible peaks in daily time spent on "social media" websites for participants in the intervention group. In contrast, participants in the control group tended to spend time on social media more uniformly across the 28 days of the study period. With regard to time spent on "YouTube", for example, participants learning under control group conditions seem to have invested more time overall, but particularly more time at the beginning of the study, whilst participants in the intervention group tended to show a somewhat delayed onset (i.e., peak occurs in the third week), but less time overall. Interestingly and rather unexpectedly, participants in the intervention group seem to have spent less time overall on websites categorised as "productivity".

As different learners will differ in the overall time spent online (depending on course and complexity of learning material, but also determined by access to the internet), a more appropriate perspective for comparing groups would be to look at relative proportions of online time spent on various website categories. This is depicted in Fig. 10. This graph shows the relative predominance of entertainment, social media, and YouTube websites in learners' daily web navigation behaviour. More than half of their total online time was dedicated to these three categories of web resources. The time commitment given to engaging with educational websites and resources that were categorised as related to "productivity" (which might be related to learning as well), accounted for only a quarter of the total time spent online.

Further inspection of Fig. 10 suggests that the proportion of time dedicated to educational web resources by participants in the intervention group is more varied over time than the relative time investment on educational websites in the control group. The intervention group's proportional time distribution seems to have two local peaks with a marked dip after day 12 until around the fourth week. The proportion of time dedicated to educational URLs by participants in the control group (who benefited from the online tool's basic functionality, i.e., no adaptive messaging) remained at roughly the same level during the study period. Overall, the time commitment to educational URLs

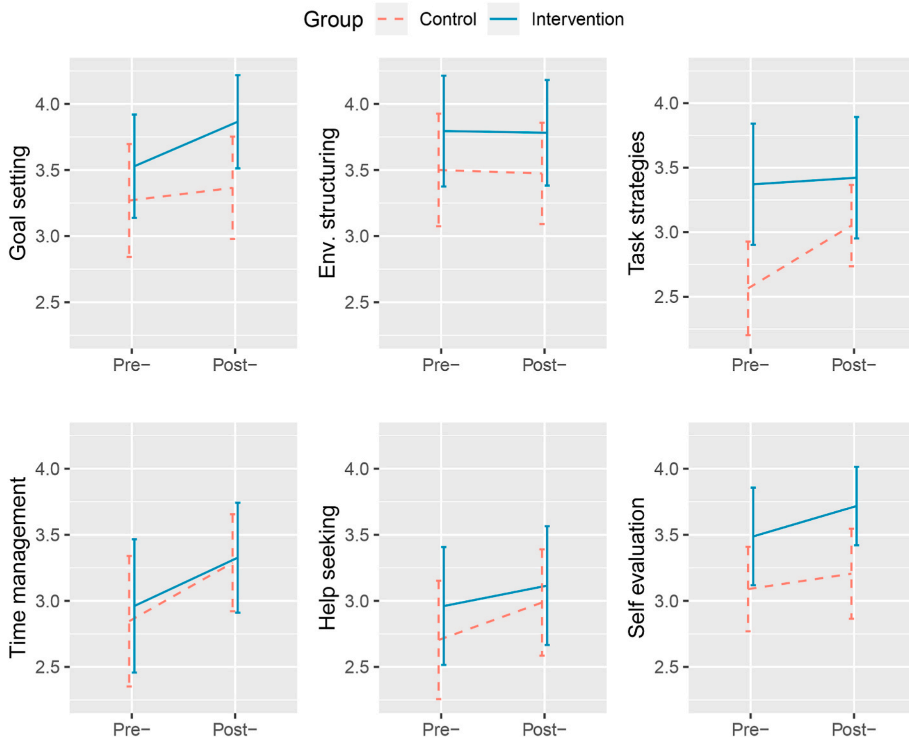


Fig. 8. Graphical representation of changes within and between groups in self-report levels of SRL.

visualised in terms of proportions for each group echoes the patterns observed earlier in absolute values in Fig. 9. In addition, this form of visualisation reveals that the relative proportion of entertainment-related websites was smaller in the first two weeks for those participants who received the adaptive assistance. The remaining categories of web resources accessed by participants remained rather stable across the period of four weeks, with only occasional minor fluctuations over time.

To better represent the dynamics of trajectories in time investment over time, we employed curve fitting procedures. A fit with four-degree polynomials seems to represent the best compromise in terms of data fit on the one hand and model complexity on the other.

Subsequently, curves with a least-squares fourth-degree polynomial fit for each category of web domains and learners' time spent online were fitted (see Fig. 11). The diagram shown at the top of the figure (panel a) suggests that the total time spent online by learners from both experimental conditions differed during the first three weeks of the study period; learners in the control group tended to have longer times of web activity per day in comparison to participants in the intervention group. Panel b in Fig. 11 depicts the difference between curves relating to learners' course websites and other "educational" URLs. Curves fitted suggest that learners exposed to the intervention tended to commit a higher proportion of their time to learning at the beginning of being exposed to the intervention than seems to be the case for the second half. In contrast, learners in the control group tended to reduce their education-related time commitment initially, but then increased this slightly towards the end of week two, followed by some minor fluctuations through to the end of the study. There is also a difference in curves on the graph relating to the "entertainment" category (see panel g in Fig. 11). The comparison of the fitted curves suggests that in the first two weeks, learners in the intervention group spent less time on websites classified as entertainment. After this initial "advantage" both groups tended not to differ in the amount of time spent on entertainment. No discernible patterns of differences can be identified for categories of URLs, such as Productivity, YouTube, Social media, and Other websites. Overall, these fitted curves suggest that the observed behaviour over time for web domains categorised as educational and entertainment have complex time varied trends, and that the effect of the intervention might not be stable across time.

4.3. The role of individual differences in responding to the intervention

This section aims to answer the third research question by exploring the role of individual differences in learners' responses to the intervention in terms of either developmental or compensatory effects on their online learning. To this end, the sub-sample of participants in each of the two experimental groups were median split according to the respective individual difference variable. These include the SRL total score at baseline as well as the five personality dimensions measured by the IPIP questionnaire. The resulting groups were contrasted in terms of the proportion of time spent visiting websites across the previously discussed categories over the course of the study period.

Fig. 12 shows the outcome of this approach for the SRL total score. Interestingly, participants with higher levels of self-reported self-regulatory skills tended to spend a higher proportion of their online time on entertainment websites, but slightly less time on social media and YouTube. When comparing control and intervention groups in terms of their relative time investment in educational and productivity related websites, it appears that the intervention in the form of the adaptive online learning assistance resulted in proportionally more time being spent on educational websites for those learners who rated themselves lower in self-regulatory skills.

Learners with higher levels of self-reported Neuroticism (see Fig. 13) seem to have spent a higher proportion of their online time on educational and productivity websites (the latter especially when provided with adaptive online assistance), and a smaller proportion of their online time on entertainment and social media websites.

As suggested in Fig. 14, a higher score in Agreeableness seemed to coincide with smaller proportions of time spent on educational and productivity websites when not receiving tailored online learning support. As previously mentioned, YouTube can serve as a tool for learning as well as a source of distraction and entertainment. For obvious data protection reasons, we have not collected data on the specific form of

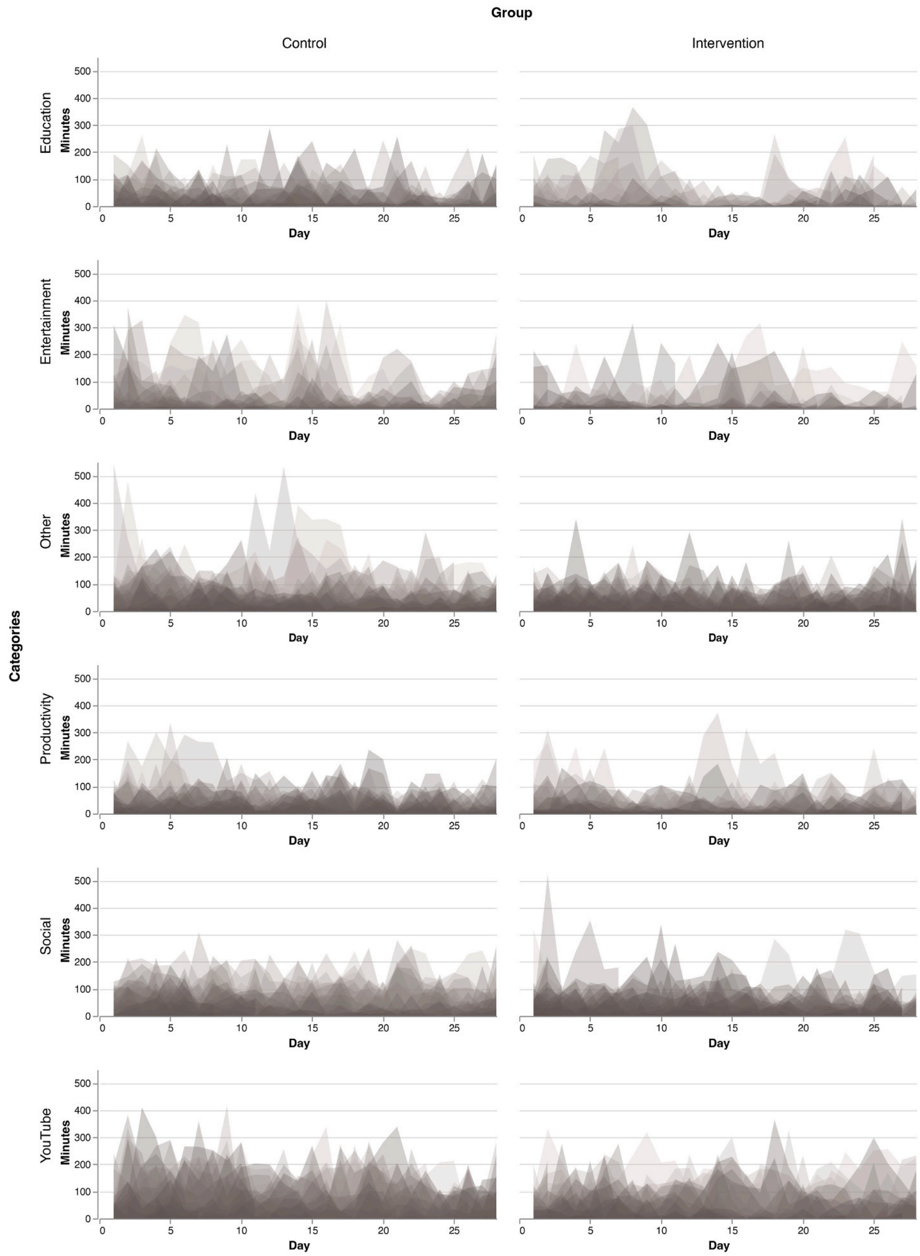


Fig. 9. Time spent by individual participants on domain categories between groups (time in minutes).

engagement with YouTube for learners participating in this study. The intervention seems to have had a positive effect on the relative amount of time spent on educational and productivity websites for those high in Agreeableness, which, as a side effect, also resulted in a lower proportion of time spent on YouTube and other entertainment websites.

Rather counter-intuitively, learners with higher levels of Conscientiousness (see Fig. 15) when only being presented with the generic component of the online assistant (i.e., control condition) tended to spend higher proportions of their online time on entertainment websites, which seemed to be at the cost of time used for educational web resources. The intervention seems to have positively affected the use of productivity-related websites. Learners with lower levels of Conscientiousness tended to respond to the intervention with an increased proportion of time spent on educational websites.

Learners who saw themselves as being low in Extraversion tended to spend a higher proportion of their online time on entertainment websites but seem to have benefitted from the adaptive assistance in terms of education related websites (see Fig. 16). This tendency does not seem to be mirrored in learners high in Extraversion (see Fig. 17).

Learners scoring low on the Openness scale seem to benefit the most from the intervention in terms of the proportion of time spent on educational websites. For those learners, the intervention seems to also increase the relative time spent on YouTube. Learners high in Openness, when not being exposed to the adaptive assistance, tended to spend most of their online time on social media and YouTube. They did, however, seem to respond to the intervention by reducing their YouTube time.

From a purely descriptive perspective, a general pattern is emerging: The intervention, in the form of behaviour adaptive messages (in contrast to the generic component of the virtual assistant in the control condition), seems to cause a more varied, heterogeneously distributed time investment where educational and productivity websites are concerned. With all necessary caution, this could be interpreted as an indicator of the intervention's effectiveness, at least on a behavioural level. In this vein of cautious speculation, the lack of a clear result pattern arising from the analyses conducted in relation to research question 2 (general compensatory effects) in comparison to the pattern

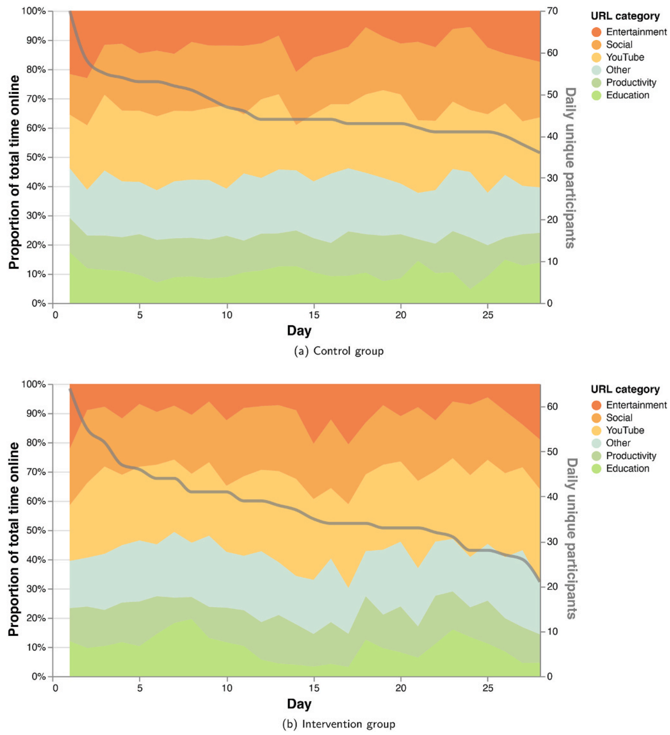


Fig. 10. Observed learners' time commitment between groups (proportion of total time spent online).

discussed in relation to research question 3 (differential compensatory effects) tends to confirm the old and sometimes overused adage that one size does not fit all. This certainly is to be expected for online learning.

5. Discussion

By using both self-report measures and trace data, this study has aimed to establish whether adaptive assistance affects a learner's level of self-regulatory skills in the form of developmental or compensatory behavioural shifts in SRL. A similar approach was taken by Jansen et al. (2020) and van Alten et al. (2020) who tested the effects of providing video interventions and prompts to support learners' self-regulation. Moreno-Marcos et al. (2020) studied how MOOC dropout rates can be predicted by self-report and behaviour data. In contrast to our study, the behavioural data utilised was limited to traces obtained within the course management system in which the online learning was offered. In our study, we evaluated the adaptive SRL support within *and beyond* learning-related activities based on learners' behaviour in naturalistic settings and self-report SRL measures. This study further advances the promising areas in AIED research, including: personalisation and feedback (Cavalcanti et al., 2021; Chen, Zou, et al., 2022; Hwang et al., 2020; Ingkavara et al., 2022), EDM for assessment and performance prediction (Chen et al., 2020; Molenaar et al., 2023; Zhang & Aslan, 2021), mitigating difficulties in attaining learners' skills (Kabudi et al., 2021), utilising AI to provide personalised scaffolding (Lim et al., 2023) and metacognitive prompts to change learners' behaviour (Raković et al., 2022), and contributes to the development of the hybrid human and artificial cognitive regulatory systems (Molenaar, 2022; Siemens et al., 2022).

5.1. Facilitation of self-regulatory skills development

We now provide a tentative interpretation of the results from this predominantly exploratory study. Due to the substantial attrition — not uncommon in longitudinal studies in online learning with voluntary participation — the analyses related to addressing research question 1 ended up having insufficient statistical power to secure higher levels of statistical certainty. Consequently, we can only claim that in the sample studied there were no large effects observed in the responses to the SRL questionnaire. The employment of the SRL questionnaire is based on the assumption that self-ratings are valid indicators of respondents' self-regulatory skills. Looking at this result in isolation carries little information with regard to the effectiveness of the intervention in terms of affecting online learners' meta-cognitive skill sets related to self-regulation. As a result, we aimed to establish whether the intervention had some systematic effects on learners' online behaviour.

5.2. Compensation for self-regulatory skills

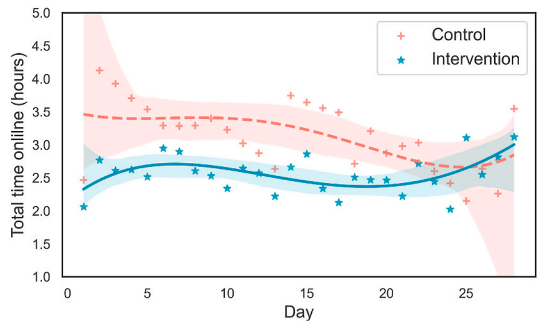
What sets this study apart from other studies with a similar focus is that the behaviour traces that were recorded go beyond what happens within the online platforms used to deliver online courses. The results in relation to research question 2, where we looked at the potential intervention effects on learners' online behaviour that might be interpreted as compensation for yet insufficiently developed SRL, suggests a clear trend towards less online time overall for learners in the intervention group. Whether this amounts to higher levels of efficiency in learning cannot be answered conclusively as we do not have access to any data that could serve as a valid proxy for learning success, as such. The tendency for learners in the intervention group to spend a smaller percentage of online time on websites classified as entertainment — at least in the initial phases of their online studies — in conjunction with spending a slightly higher proportion on educational websites, lends some tentative support to an efficiency-focused compensatory effect of the adaptive online learning assistant. This finding, and its admittedly speculative interpretation, awaits replication in more targeted experimental studies.

5.3. The role of individual differences in compensatory and developmental shifts in learners' self-regulation

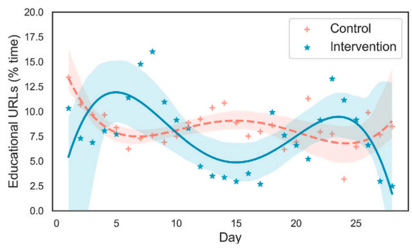
To further qualify these general compensatory effects of the intervention, we then explored whether learners' characteristics (i.e., individual differences) resulted in differential patterns of behavioural changes as a response to the intervention (research question 3). This perspective hints at some further insights regarding the differential effectiveness of the intervention in the form of the employed adaptive online learning assistant.

Interestingly, and hence calling for clarifying replication, behaviour traces seem to contradict self-rated SRL as learners who scored higher in SRL tended to generally spend higher proportions of their online time on entertainment websites. Learners on the opposite side of the SRL continuum seemed to respond well to the intervention, as indicated by their increase in time spent on educational websites.

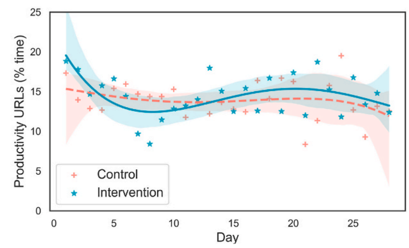
When attempting to synthesise the descriptive findings related to the five personality dimensions, we needed to consider that they are often empirically interrelated (e.g., Conscientiousness tends to be negatively correlated with Neuroticism at the group level). As would be expected, learners with higher levels of Neuroticism tended to spend proportionally more time on educational and productivity websites, whilst learners low in Neuroticism tended not to respond to the intervention. The observation that learners rating themselves as high in Agreeableness tended to spend little time on educational websites and considerably more time on YouTube when "left alone" might encourage the view that high levels of Agreeableness in online learners could represent some sort of a risk factor that an adaptive online learning assistant could help mitigate (given the increased proportion of time on educational and productivity websites). In this context, we need to be reminded of the fact that it was higher levels in Agreeableness that characterised those participants who tended to stay engaged in the study and the data collection "chores" associated with it. On the other hand, learners with low levels in Agreeableness tended not to benefit from the intervention.



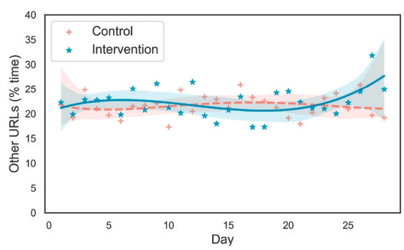
(a) Average daily total time spent online between participants' groups



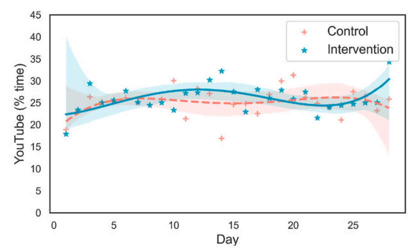
(b) Educational websites



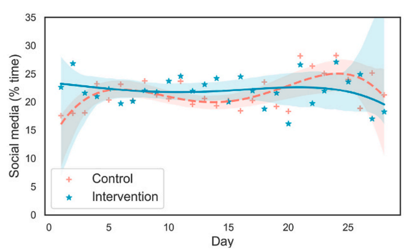
(c) Websites categorised as "Productivity"



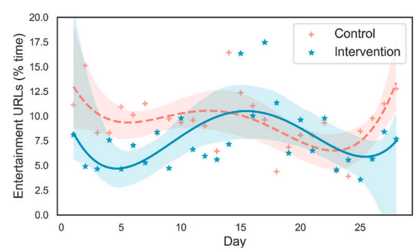
(d) Uncategorised websites ("Other")



(e) YouTube



(f) Social media websites



(g) Websites categorised as "Entertainment"

Fig. 11. Curves with polynomial fits for each category of web domains.

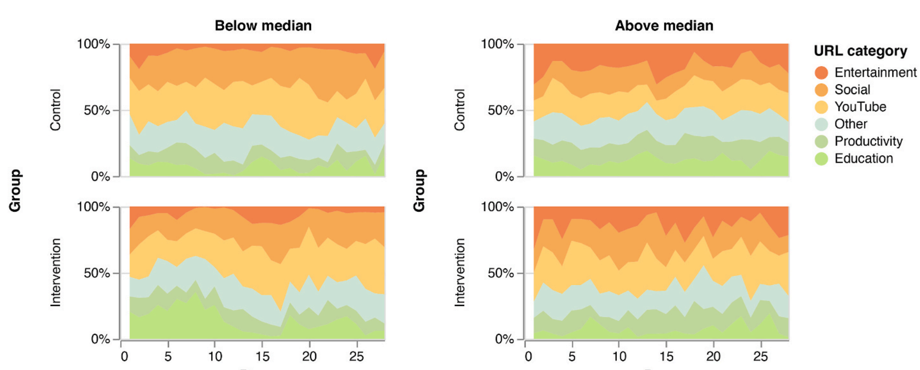


Fig. 12. Differences in behavioural responses to the intervention contrasted for learners low and high in SRL measured at baseline.

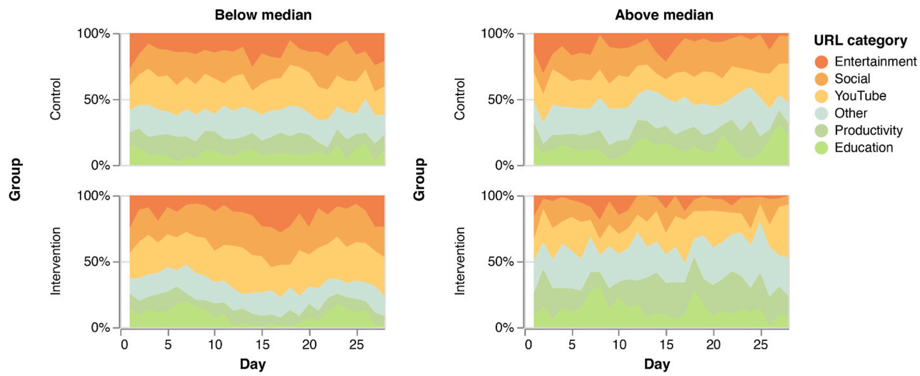


Fig. 13. Differences in behavioural responses to the intervention contrasted for learners low and high in Neuroticism.

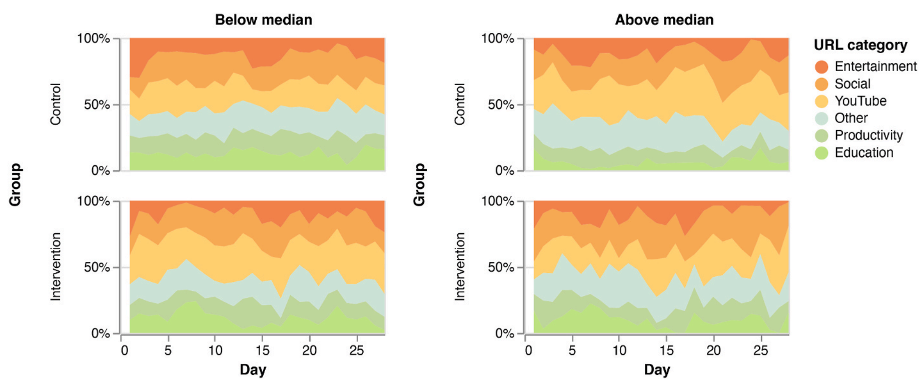


Fig. 14. Differences in behavioural responses to the intervention contrasted for learners low and high in Agreeableness.

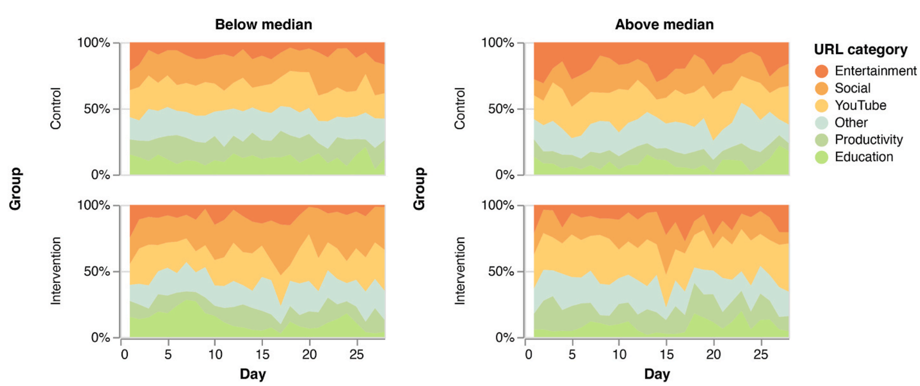


Fig. 15. Differences in behavioural responses to the intervention contrasted for learners low and high in Conscientiousness.

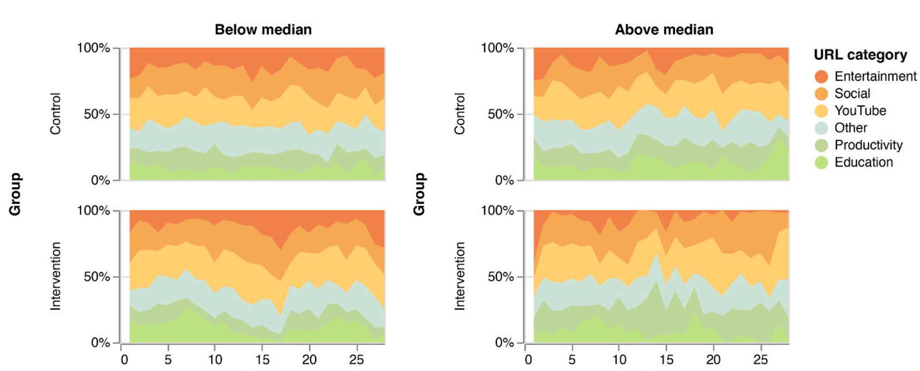


Fig. 16. Differences in behavioural responses to the intervention contrasted for learners low and high in Extraversion.

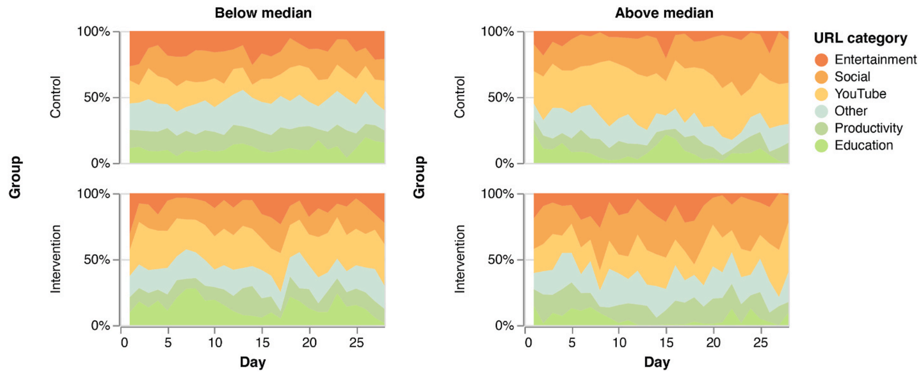


Fig. 17. Differences in behavioural responses to the intervention contrasted for learners low and high in Openness.

The exposure to the intervention seems to have resulted in behavioural changes in learners low in Extraversion, Openness, or Conscientiousness.

As an observable effect of the intervention, participants' time commitment to educational web resources surged in the first ten days and declined thereafter until the end of the third week. This was especially noticeable for learners with scores below the median in the self-report overall baseline for self-regulation and conscientiousness. There are two possible explanations for this result. First, the novelty of the intervention may have had an initially positive impact, which decreased as learners grew used to the tool. A second possible explanation is that the learners in the intervention group contributed more extended learning time in the first 2 weeks as indicated by several learners in the intervention group having prolonged learning sessions during a single day, with up to 5 h of time spent on educational URLs (see Fig. 9), whilst time on educational URLs in the control group rarely exceeded 3 h per day. Thus, learners from the intervention group, with increased effort in the early days of their study participation, may not have required as much effort in subsequent days to master their learning material. This is especially relevant for self-paced MOOCs, which usually do not include strict timelines.

5.4. Generalisability and limitations

The high attrition rate of responses to the post-intervention SRL questionnaire limits the generalisability of the findings. In future studies — where attrition can be minimised more effectively — a higher level of precision and/or density of trace data recording might be employed. This would allow for the utilisation of more sophisticated data analysis strategies. An involvement of more than one or two domain experts for judging and categorising learners' online behaviour could benefit the identification of personalised intervention options that promise maximum effects on the individual learner's behaviour. In the study presented, the evaluation of the compensatory function of the intervention was exploratory. Future studies might venture into testing effects with a stronger inferential focus and seek to replicate the results presented here. Likewise, further studies might seek to reduce attrition by employing shorter questionnaires and collecting responses from participants more frequently (e.g., by asking participants to provide weekly self-reports). Also, recurring participants from a single MOOC supplemented by participants' data from the MOOC provider could improve homogeneity in terms of learning content and learning context and subsequently could help to shed further light on any additional variables that might affect changes in learners' self-regulation. Further, to minimise sampling bias, the application of the intention-to-treat analysis and the utilisation of multi-level growth modelling might be beneficial.

5.5. Theoretical and practical implications

In the conceptual underpinning of our study, we made the distinction between the developmental effects and the compensatory effects an intervention might have. The former is conventionally measured using self-reports (i.e., the use of questionnaires). The latter, however, is probably better captured in terms of behavioural changes. The rationale behind such a distinction is that the development of a multidimensional set of skills such as SRL is a complex, delayed, and non-linear process. By relying on self-report data alone, especially in the context of relatively short intervention periods, onsets of those change processes are likely to be overlooked. Most interventions related to online learning, even those targeting a meta-cognitive skill such as self-regulation, aim at modifying behaviour. Hence, the earliest signals of change should be expected on that level. Only when these changes are sufficiently established in a learners' behavioural repertoire (i.e., when certain learning behaviours have become habitualised), might we then expect them to be reflected in their self-ratings, too. In short, the perspective taken in our study is to allow potential intervention effects to manifest themselves at the level of compensatory behavioural shifts before expecting them to be detectable in self-ratings.

The results of this study might be of particular interest, in terms of practical implications, for online learning platforms, online course developers, and designers of web applications that aim to support online learning. The findings from this study can provide some (at least preliminary) pointers for the development of adaptive interventions as part of online learning environments beyond specific online course platforms and learning management systems. The research reported and the results obtained in our study have the potential to contribute to a better understanding of the effects of the interplay between the situational characteristics across longer-term learning episodes and learners' individual differences in cognitive and non-cognitive attributes in response to the adaptive assistance as an intervention. Such understanding will be instrumental in the efforts to improve the quality of MOOCs, including addressing MOOC learners' concerns or complaints effectively (Chen et al., 2021). The present study might further encourage course designers to include behaviour measurements in addition to self-report data on learners' SRL in order to obtain more precise estimates of their learners' SRL levels, as this will ultimately increase the effectiveness of the self-regulatory support provided. This study has provided a promising example of how tracking learners' web navigation behaviour, in combination with their self-report data and responses to the adaptive assistance intervention, can facilitate the measurement of learners' self-regulation beyond their course platforms.

5.6. Future directions

Future research might consider including the application of multimodal learning analytics to supplement behaviour trace data with data from other sources. Combining multiple data sources is an especially promising avenue for future research in the realm of the growing role of augmented reality, virtual reality, and mixed reality technologies in education with their novel data sources regarding human-computer interactions and computer-assisted learning (Chen, Xie, & Li, 2022).

To better understand the potential mechanisms of the intervention, more targeted and systematic evaluations from different intervention components are needed. Such investigations could utilise response surface analysis methodology (He & Côté, 2019) and the application of non-parametric trajectories for time-varying effect modelling (Dziak et al., 2015). To optimise the adaptive assistance intervention, its individual components could be evaluated in separate studies. A range of analytic procedures and research designs could be applied, including factorial and fractional factorial randomisation trials (Collins, 2018), sequential multiple assignment randomisation trials (NeCamp et al., 2019), and micro-randomisation trials (Klasnja et al., 2015). For example, emerging analytical approaches evaluating data resulting from micro-randomisation trials allows us to study within-individual correlations of responses and the time-varying effects of such interventions. In addition, based on an evaluation of the interventions' attributes and learners' individual differences, the contents of the notification messages contained in an adaptive assistance intervention can be further personalised with the application of corpus linguistics, for example, by applying chatbots to generate individually tailored messages as intervention options to support learners' self-regulation.

In future AIED and EDM studies, the assessment of learners' self-regulation, identification of procrastinatory behaviour, and delivery of the intervention could be improved in two key ways. First, an assessment could be performed to establish the baseline level of self-regulatory skills, indicating an intercept and a slope for the estimated effects of a self-regulatory intervention. This task could be supplemented by correlational analyses between self-report and behavioural data. For example, Least Absolute Shrinkage and Selection Operator (LASSO) linear regression can be applied to URLs visited by learners to identify associations between self-report levels of self-regulation and visited URLs, analogously to research on predicting personality traits based on Facebook likes conducted by Kosinski et al. (2013). Second, an assessment based on behaviour traces and expert coding could identify early onsets of potential problems in learners' self-regulation and direct approaches to prevention. For example, sequential pattern mining methods, such as the pattern-growth algorithm PrefixSpan (Fournier-viger et al., 2017), can be utilised to identify frequently appearing patterns of web navigation behaviour, which can then be attributed to different states of self-regulation by human experts. In addition, statistical learning approaches can be applied to supplement this assessment. For example, "long short-term memory" recurrent neural networks can be applied for predicting learners' web navigation behaviour. Utilising both approaches (identification of frequently appearing patterns of web navigation behaviour associated with procrastination; prediction of web navigation behaviour) could provide orientations for prevention, i.e., interventions before the problematic behaviour occurs.

The prediction of web navigation behaviour, identification of self-regulatory patterns, and intervention delivery based on these two steps poses ethical risks. Incorporating interventions into the learning process may not work as intended, and it may change learners' attitudes and behaviour in unintentional ways, or the long-term effects might be different from the observed proximal outcomes. Interventions may be perceived as violating learners' personal autonomy, similarly to AI-powered personalisation in MOOC learning, as discussed by Yu et al. (2017). Therefore, the ethical risks of applying research on behavioural change, coupled with novel approaches in statistical learning, such as applying black box AI systems in intervention design, require further in-depth ethical examination, which could be another important focus for future studies.

The descriptive and cautiously speculative account given here should be seen as an attempt to instigate new lines of inquiry or even to facilitate the generation of testable hypotheses to be addressed in specifically designed experiments notwithstanding the challenges of implementing rigorous experimental research in the context of online learning, a label conveniently used for a wide variety of activities taking place under a wide variety of circumstances.

6. Conclusion

The virtual learning assistant employed in this study represents a novel approach to delivering adaptive support in online learning environments. Helping learners to utilise the opportunities provided by online learning and to become successful lifelong, self-determined learners, the virtual assistant combines the assessment of self-regulation via self-report and behaviour traces in settings resembling online learners' daily routines and circumstances in a minimally invasive fashion. The learning assistant also allows the evaluation of proximal outcomes of the intervention to be examined at different levels of detail. The main conceptual contribution of this work presented here is in its differentiation between long-term developmental effects and mid-to short-term compensatory effects on online learning. The conceptually informed framework and methodology laid out in this study also highlight the necessity for integrating the notion of individual differences of learners for the facilitation of an effective intervention. In more general terms, the study presented here demonstrates the considerable potential of educational interventions utilising advances in behaviour, cognitive, and constructivist approaches to learning enhanced by AI and human intelligence hybrid support systems.

Ethics

Prior to data collection, each participant was asked to read an information sheet outlining the study. They were asked to agree with a written declaration of informed consent. Ethical approval for this study was obtained from Durham University's School of Education (date of approval: 17 January 2019).

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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