Assessment, development and experimental evaluation of self-regulatory support in online learning

POGORSKIY, EDUARD

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Eduard Pogorskiy

Abstract

Online learning requires a higher level of self-regulation than face-to-face learning. Learners are likely to differ in their cognitive, metacognitive, affective or motivational resources to meet this demand. Individual differences in self-regulation is one major factor contributing to success or failure in online learning, other factors include characteristics of the online learning environment and the complexity of the learning content itself. Lack of self-regulation is likely to affect learners' engagement with the course content, may result in sub-optimal learning outcomes, including failure to complete the course. A virtual learning assistant has been designed and developed to support online learners. This research aims at ascertaining the effectiveness of providing adaptive assistance in terms of (a) compensatory and (b) developmental effects. Online learners involved in the empirical part of this study ($N = 157$) were randomised into one of two experimental conditions. For the intervention group, the online learning assistant provided personalised in-browser notifications. This feature was disabled for the learners in the control condition. Results indicate that the adaptive assistance did not result in noticeable developmental shifts in learners' self-regulation as assessed via conventional self-report measures. However, learners allocated to the intervention group spent less time online per day in first three weeks of being exposed to the adaptive assistance, reduced their time commitment to entertainment websites during first two weeks, and increased their engagement with educational web resources during the first ten days. In addition to the time-varying effects, these compensatory (behavioural) shifts were moderated by learners' individual differences in personality. The outcome of this study suggests that the utilisation of a virtual learning assistant that provides adaptive assistance can be effective in compensating for not yet developed self-regulatory skills, and subsequently help facilitating success in learning on short online courses.

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List of Abbreviations

AI Artificial Intelligence. 12

AR Augmented Reality. 16

BCT Behaviour Change Technique. 76

CHC theory Cattell–Horn–Carroll theory of intelligence. 33

CPS Complex Problem Solving. 4

FFT Five-Factor Theory. 37

ICT Information Communicative Technologies. 7

IE Instrumental Enrichment. 28

IPIP International Personality Item Pool. 99

IQ Intelligence Quotient. 33

JITAI Just-in-time Adaptive Interventions. 75

LMS Learning Management System. 53

mHealth Mobile Health. 12

MLE Mediated Learning Experience. 28

MOOC Massive Open Online Course. 9

MOST Multiphase Optimization Strategy. 75

MRT Micro Randomised Trial. 75

PTS Person, Task, and Situation framework. 15

RCT Randomised Controlled Trial. 13

SRL Self-Regulated Learning. 41

VR Virtual Reality. 16

WM Working Memory. 33

ZPD Zone of Proximal Development. 24

Statement of Copyright

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1 | Background and Introduction

1.1 Problem statement

The 21st century has brought with it various social opportunities and challenges: advances in science, increased life expectancy, the benefits and dangers of artificial intelligence, the gig economy, job insecurity, economic inequality, emerging and diminishing occupations, political uncertainty, the rise of populism and fall of cosmopolitanism – to name just a handful. A number of these changes have occurred during the last two decades, however, humans have always been able to cope with change, through our ability to learn how to adapt and to deal with uncertainty. We learn as a society as a whole, within social groups and as individuals.

Education plays a vital role in facilitating the learning process and developing necessary skills. Through advances in the understanding of the learning process, the field of education has undergone crucial changes and is facing novel challenges. These include (1) practical concerns, such as lifelong learning (Alheit, 2018; Biesta, 2013), the development of 21st-century skills (e.g. complex problem solving, self-regulation; for the full list of skills, see, for example, Geisinger, 2016; van Laar, van Deursen, van Dijk and de Haan, 2017), and the implementation of evidence-based education (Slavin, 2002); and (2) pastoral concerns: the involvement of underrepresented groups of learners (Lambert, 2020), and the elimination of educational disparities (Paulsen and McCormick, 2020), to name but a few.

Educational providers are now entering a global market, going beyond national borders to expand their presence and attract learners around the globe (Shattock, 2017). Universities are, rather than facing competition solely amongst each other, now competing with EdTech companies that have actively entered the educational market (Selwyn et al., 2020). Technological advancements, alongside advances in understanding learning processes, have opened up multifarious opportunities for education. One crucial advance is that educational programs can now be scaled to a vast, global student body (Kizilcec et al., 2020).

However, this new educational model, whereby courses are scaled to provide educational content online to millions of learners around the world, also presents complex challenges. The problem is that online learning environments are characterised by increased exposure to distractions (Robal, Zhao, Lofi and Hauff, 2018), coupled with a relative lack of support (Reich and Ruipérez-Valiente, 2019). In order to overcome these challenges, learners need to effectively use their self-regulatory skills—one of a range of options that are crucial to educational success (Reparaz, Aznárez-Sanado and Mendoza, 2020). Self-regulation in learning can be defined, in broad terms, as a contextualised and dynamic process used by individuals during attempts to purposefully initiate, manage and adapt their pursuit of set goals (Cleary and Callan, 2018, p. 338). Self-regulation plays an essential role in facilitating the learning process. It helps learners to master new learning materials, persist with their study of educational content, and to achieve their ambitions as lifelong learners (Nussbaumer, Dahn, Kroop, Mikroyannidis and Albert, 2015). This research will focus on self-regulation as a crucial means by which learners may take advantage of the opportunities provided by contemporary online learning and will carefully examine how learners can both acquire and effectively deploy this skill.

1.2 Learning as process and outcome

Learning, considered as a process and as an outcome, involves many sub-processes and components. In general, learning is the result of transferring knowledge and skills from one individual to another, from environments to an individual, or the result of internal mental processes based on acquired experience. However, many modern approaches to learning are driven by conceptualisations set forth by Jean Piaget (Furth, 1987; Piaget, 1952), Lev Vygotsky (1978), and Carl Rogers (1969), whose ideas stem from pragmatist and interpretivist epistemological traditions in order to define learning, as discussed in detail by Marcy Driscoll (2005) and George Siemens (2005). Knud Illeris, known for his work on project studies in theory and practice from the 1970s onwards, offers a broader definition of learning as 'any process that in living organisms leads to permanent capacity change and which is not solely due to biological maturation or ageing' (Illeris, 2007, p. 3). Dale Schunk, an educational psychologist, has offered another definition, whereby learning is understood as 'an enduring change in behaviour, or in the capacity to behave in a given fashion, which results from practice or other forms of experience' (Schunk, 2012, p. 3). However, learning does not necessarily result in observable behaviour, and learning can be understood from many different theoretical angles, including foundations proposed in behaviourism, cognitivism, constructivism (Ertmer and Newby, 2013), and in more recently developed ideas of connectivism (Siemens, 2005).

Research on learning refers to the examination of how people learn, encompassing several key areas: conceptual theorisation, contextual aspects of learning, their applications in practice (Mayer, 2018), and learners' affective, cognitive, and conative aspects. As explored by Illeris (2018), learning includes external interactions and internal processes, managing learning content and processing incentives in order to generate the mental energy necessary to run learning processes effectively. The aim of the learning process is to be able to construct meanings, deal with novelty and to develop overall personal functionality. The outcome of the learning process refers to changes in learners, such as changes in reasoning ability, information processing capacity, motivation, working memory, experience, and knowledge. These changes reflect a learner's readiness to handle novel and complex tasks in a range of environments and circumstances (Beckmann, Birney and Goode, 2017), resulting, in their turn, in changes in learners' behaviour. Educators, learning instructors, and educational psychologists have long debated the possible ways to develop an effective and efficient solution to support these changes and accurately measure the occurrence and progress of such changes in learners. Educational interventions address the former, while assessment for learning (i.e. formative assessment) aims to address the latter.

Early debates on individual differences and the underpinnings of learning have led to the prevalence of measuring differences in intellectual ability and human capacity across individuals, known as human intelligence. Almost a century's research on intelligence, beginning with the pioneering work of Alfred Binet and

Theodore Simon and culminating with the three-stratum theory of cognitive abilities proposed by John Carroll (Wasserman, 2018), has led to the understanding that while general high-level predictors of success at school can be determined, some intellectual abilities are malleable and can be enhanced through educational interventions. There are, more particularly, specific (low-level) abilities that are susceptible to intervention (Carroll, 1993). Surprisingly, nearly half of large-scale experiments conducted in the United Kingdom and the United States failed to prove that educational interventions can help improve learning outcomes (Lortie-Forgues and Inglis, 2019). Several reasons may have affected the outcomes of these studies, but it is likely that the interventions analysed did not adequately address the root causes of the issues considered. In addition to this limited evidence for the productivity of intervention, their implementation is often complicated, due to the multifarious contexts and complexities of learners' internal processes associated with learning.

To evaluate the effects of education, educational psychologists have developed a range of techniques and instruments to assess learning processes (cognitive processes during learning) and learning outcomes (knowledge and skills), as well as learners' characteristics (Mayer, 2018, p. 176). In addition to standardised forms of assessment such as psychometric tests, advances in research and practice have brought to light other forms of assessment such as dynamic testing and assessment (Elliott, Resing and Beckmann, 2018), response to intervention evaluations (Grigorenko, 2009), stealth assessment (Shute and Ventura, 2013), and instruments to assess learners' abilities in Complex Problem Solving (CPS) and general intelligence. CPS is a broad term used in research, learning and assessment contexts that refers to an individual's ability to deal with novelty and to utilise cognitive resources in a learning environment (Beckmann and Goode, 2017). CPS, as an alternative to traditional intelligence tests, is considered a more accurate and reliable measure of one's ability to benefit from learning: 'if knowledge is acquired in a CPS situation, then the amount of knowledge acquired is more likely to be predicted by a subject's learning ability than by the subject's traditional intelligence score' (Beckmann and Guthke, 1995, p. 196). These forms of assessment have emerged in response to a current challenge in the field of educational psychology: to develop an efficient and valid technique to assess individual differences in prior knowledge, motivation, and metacognition, which can be utilised to support instruction (Mayer, 2018).

1.3 Evolution of learning

1.3.1 The traditional classroom and blended learning

This section describes the development of key theories of learning and their evolution over time in order to highlight their complex histories, taking note of how knowledge, learning, and educational practices to support learning transfer have been understood over time. Modern understanding of learning are rooted in two views: the first considers knowledge as based on experience — empiricism; the second considers knowledge to derive solely from reason, whereby the criterion of truth is not sensory — rationalism. Both views of learning and knowledge acquisition are rooted in a rich philosophical history, ancient Greek philosophy and its traditions. Plato's heritage is being attributed to rationalism, and Aristotle's ideas referred to empiricism (Ertmer and Newby, 2013). These ideas were further developed by British Empiricists (Bacon, Locke, Berkeley, Hume) and German idealists (Kant, Fichte, Schelling, Hegel). These advances in conceptualisation of learning led to three dominant perspectives on the learning process in the 20th century: Behaviourism, Cognitivism and Constructivism.

Alongside breakthroughs in the ways in which learning is understood and conceptualised, there have also been crucial developments in how the learning process is applied in practice. Advances in other scientific fields, alongside corresponding political and societal changes have influenced views on the learning process and its role in education. For example, in tandem with the rise of machine-labour during the industrial revolution, the same principles of manufacturing and automation emerged in education, and principles of behaviourism played a key role in it. Ertmer (2013), examines behaviourism and its key principles from a constructivist position, equipped with ideas from the cognitive revolution. From this point of view, behaviourism is understood as changes in observable performance prompted by a demonstrated response to a specific environmental stimulus. According to the behaviouralist model, a learner is viewed as a subject of environmental conditions, rather than an active participant of a learning process (Ertmer and Newby, 2013).

Varied scientific advances, such as those made in computational science and information processing, the proliferation of studies focusing on human perception, thinking and cognition have accompanied reforms in education (Bruner, 2018). According to cognitive theories, learning more closely relies on rationalism, and learning outcomes tend to be represented as the product of changes in acquired knowledge, rather than changes in a possible response. The process of knowledge acquisition, its internal underpinnings, and learners' participation in this process all have a particular attention in cognitivism (Ertmer and Newby, 2013).

With the rise of constructivists ideas, the focus in education has correspondingly shifted from the teacher to students. A traditional classroom becomes a constructivist classroom with all its associated features. These characteristics include an understanding that the learning process itself and reflections on it are as important as the achieved results, flexibility surrounding the curriculum, a focus on learners' creativity, an interactive teacher's role, and the assumption that knowledge is a dynamic construct (Aqda, Hamidi and Ghorbandordinejad, 2011; Le Cornu and Peters, 2005). To summarise, the constructivist's view of the learning process is that it is determined by an extension of the principles of cognitivism, whereby learning is considered to be the product of mental activity. At the same time, the constructivist's view is in conflict with that of the behaviourists and extreme cognitivists on the point that knowledge is mind-dependent and built upon our internal interpretations of received experience (Ertmer and Newby, 2013).

The development of learning theories, and particularly the rise of constructivist ideas, has contributed to changes in educational discourse. As remarked by Biesta (2013), it has led to a culture of 'learnification' in education, and the rise of a 'new language of learning', picked up by politicians, the Tech-Ed industry and media. The excessive theorisation of the learning process and the presence of often contradictory views on the same processes has resulted in a reactionary antagonism, with critical views towards this shift emerging in educational discourse:

> Perhaps, the fundamental problem with the bullshit of education and technology is what Frankfurt identifies as the inherent disconnect from 'how things really are'. For example, the past 100 years show that education has been largely untransformed and undisrupted by successive waves of technological innovation. Empirical research has remained resolutely equivocal about the 'learning' that can actually be said to result from the use of digital technologies. So why then is there a continued preference for referring to these and other aspects of education and technology in a manner that ignores their complex realities? (Selwyn, 2016)

A similar discussion has appeared in educational psychology:

> We have learned that our field is set back when theory building is no longer based on evidence gleaned from scientifically sound studies but rather becomes an exercise in building untestable doctrine to which educational practices must adhere. From my vantage point, it appears that a bright future depends on our commitment to taking a scientific approach, in which educational practice is based on research evidence and research-based theory, rather than a doctrine-based approach, in which educational practice must conform to the slogans of popular "isms". (Mayer, 2018, p. 177)

As Ertmer (2013) notes, despite similarities between approaches and their distinguishing features, it is beneficial to look at a problem from different angles or different theoretical positions while addressing practical learning problems. The classical university model has historically been the answer to the problem of knowledge transmission. This design has developed at pace with the increase in accessibility and popularity of technologies among educators, and new opportunities have arisen in education. As Biesta (2016) discusses, Information Communicative Technologies (ICT) provides powerful tools for education, but, most importantly, it brings education beyond schools or formal settings. With new technologies, such as gadgets and electronic devices, instructors have started to adopt tools to enhance learning, for example, using mobile apps, electronic books, digital pens, electronic whiteboards, and implementing virtual and augmented reality in a classroom.

1.3.2 Distance and online learning

In response to social changes, such as increased cost of education and changes to the workplace, educators have had to provide flexible opportunities for learning. Offering programs for distance learning would be one such example. Concurrently, due to the demands of industrialisation for workers with specific training, distance learning has become an increasingly valuable option for the great numbers of individuals who wish to access education. With increased accessibility via electronic computing devices, universities have started to provide distance education through online learning, rather than traditional correspondence courses. Increasing access to the Internet and telecommunication networks has further boosted opportunities for distance education, supplemented by e-learning technologies. Indeed, even more educationally conservative programs, such as degrees in medicine, have began to offer some online modules.

Online education has made it possible to recruit a broad range of learners, which, coupled with the characteristics of web technologies, brings unique challenges to learning and changes the population of learners. In response, new theories of learning started to emerge at that time. Siemens's (2005) research has set the stage for further exploration, listing modern problems associated with learning. Among this list are the following issues: learners move across different fields during their lifetime, informal learning becomes an essential part of the learning process, learning is continuous, technology affects learners, learning transfer overlaps across organisations and individuals, and, finally, many of the processes proposed by cognitive theorists that constitute learning can now be supported by technology. For example, with the help of artificial tutoring agents, the learning process can be decomposed to evaluate the efficacy of different types of practice for different types of students (Beck, 2006). In his work, Siemens (2005) proposes a learning theory of Connectivism, which is now recognised as one of the most prominent of the network learning theories for digital learning environments (Gerard and Goldie, 2016). With Siemens's work in mind, the main tenet in education, given the challenges mentioned above, is to consider learning as a process that is not entirely controlled by an individual and occurs within a range of environments of learning elements. Siemens defines learning as actionable knowledge that can be external to a learner, where the focus is on connecting specialised information sets, and where the ability to learn more is more critical than the present state of knowledge.

1.3.3 Online learning at scale

Within the initial aim to collectively advance education through open technology, open content, open knowledge and the creation of open learning resources (Iiyoshi and Kumar, 2008), some universities began publishing their course materials online. Online access to course materials aimed to give learners around the world the opportunity to take advantage of freely available materials, which were traditionally only available to a small cohort of selected students. This process was supported by the increasing capacity of compatible technologies, a growing demand for education worldwide, and advances in technology-mediated learning environments. These changes resulted in significant educational developments, including the creation of influential online platforms such as OpenCourseWare and Open Learning Initiative.

The next milestone in online learning was achieved with the advent of Massive Open Online Course (MOOC). The term first appeared to describe a novel phenomenon in education: a course taught online and open to the public. The first MOOC was led by George Siemens and Stephen Downes in 2008; it was open for public enrolment and attracted thousands of learners. In conjunction with universities' initiatives to open educational resources to the public, the MOOC format of learning led to pioneering online platforms such as EdX, Coursera, Udemy and Futurelearn. These platforms contributed to the mass spread of MOOCs worldwide, resulting in two widely used approaches — or branches — of teaching practices: cMOOC and xMOOC. The xMOOC model is based on instructionalist, teacher-focused structures, and cMOOC with connectivist values placed at its core and focused on peer-to-peer interactions among learners. There are a number of examples of successful MOOCs with thousands of learners utilising both approaches. For instance, there are several examples of xMOOCs with enrolments ranging from hundreds of thousand to more than one million online learners (e.g. 'Machine Learning' on Coursera and 'Understanding IELTS: Techniques for English Language Tests' on Futurelearn). An example of a successful cMOOC is the Startup School MOOC, organised by an American seed accelerator where thousands of participants, in addition to watching pre-recorded video lectures, are allocated into small groups (usually consisting of 4-8 participants) for weekly group sessions.

The transformation of learning at scale was accompanied by changes in many other areas of digital technology. With the increased performance of audio and video capturing devices, on-demand cloud-based computing infrastructure, such as Amazon Web Services and Google Cloud, wider high speed broadband connection coverage. These changes have been complemented by further government legislation to increase the level of media and information literacy, and to provide access to the Internet in remote areas as a basic need (Frau-Meigs and Lee, 2016; Frau-Meigs, Velez and Michel, 2017). Through these developments, online learning has increased access to learning opportunities (Mcauley, Stewart, Siemens and Cormier, 2010). For example, microlearning environments (i.e. micro MOOC) have been designed to deliver MOOC content using mobile platforms (Sun, Cui, Yong, Shen and Chen, 2018).

This technological shift in methods of knowledge distribution have been met with both enthusiasm and much criticism. One of the undeniably positive effects is that this novel approach enables formerly unrepresented learners to access learning resources. In 2013 Michael Crow, then president of Arizona State University, promisingly wrote about the groundbreaking aspects of MOOCs in *Nature*: 'The revolutionary aspect of MOOCs is their potential to reach millions of learners who are not enrolled in colleges and universities' (Crow, 2013, p. 276), adding, 'I believe that online learning will enable the creation of high-speed and possibly more efficacious multi- and interdisciplinary teaching environments around the world' (p. 277).

Investment in creating and developing MOOCs by universities and the challenges that arise alongside learning at scale have resulted in increased research interest in the field. This has led to a number of new research fields that aim to advance understanding of the learning process in these new settings, including learning analytics (Gašević, Dawson and Siemens, 2015; Siemens, 2013), educational data mining (Dutt, Ismail and Herawan, 2017; Romero and Ventura, 2010), and learning at scale (Bederson, Russell and Klemmer, 2015; Joksimović et al., 2018; Roll, Russell and Gašević, 2018), to name a few. Research on MOOCs has gradually shifted from early correlational studies of measures of activity and proxy outcomes to more sophisticated measures and modelling of learning (Gasevic, Kovanovic, Joksimovic and Siemens, 2014; Reich, 2015). The research community in this area is actively growing, and interest in this topic is on the rise. Research on these topics frequently appears in special issues of established journals (e.g. *Computers & Education*), while there are several newly-established specialised research journals in the field, e.g. *Journal of Learning Analytics*, *Journal of Educational Data Mining*, *Journal of Artificial Intelligence in Education*. Similarly, long-running conferences now often include panels, round-tables and streams addressing modern challenges in contemporary education. A number of regular conferences have been established, including *Educational Data Mining (EDM)*, *Learning Analytics and Knowledge (LAK)*, *European conference on Technology Enhanced Learning (EC-TEL)*, *Learning at Scale (L@S)*, *Artificial Intelligence in Education (AIED)*. Learning at scale has become an important research pathway with the focus on improving learning and providing varied opportunities and challenges for researchers through its transformation of traditional and established forms of education, from solely classroom-based models to distance, and online learning.

Learning at scale as a form of delivering education has its obstacles, which can limit the effect of learning opportunities and bring disappointments to educators, as indicated below. Learning at scale was initially seen as a movement with revolutionary possibilities, enabling the democratisation of world-leading educational practices and shifts in the conservative system of education (Hansen and Reich, 2015), which is now seen as an extension of the traditional university-based paradigm, due to obstacles associated with it. One of the main challenges for learning at scale is a low completion rate, associated with a lack of support for learners. For example, typically only 5-10% of enrolled students complete their chosen course, and the exact number depends on several factors, such as the learner's country of origin (Kizilcec, Saltarelli, Reich and Cohen, 2017). In their Policy Forum published in *Science*, Reich and Ruiperez-Valiente (2019) summarised findings drawn from prior studies on supporting MOOC learners (Xu and Jaggars, 2014; Xu, Solanki, McPartlan and Sato, 2018). Reflecting the current state of the MOOC initiative, and its struggle to meet its initial aim to reach masses of learners who are not enrolled in formal tertiary education, Reich and Ruiperez-Valiente came to the conclusion that:

> By most indications, students typically do worse in online courses than in on-campus courses, and the challenges of online learning are particularly acute for the most vulnerable populations of first-generation college students, students from low-income families, and underrepresented minorities. If low-cost, MOOC-based degrees end up recruiting the kinds of students who have historically been poorly served by online degree programs, student support programs will be vital. (Reich and Ruipérez-Valiente, 2019, p. 131)

Therefore, the authors consider MOOCs, in their current state, to be viable only as an additional resource to support those who already enrolled in education, due to the expenses associated with supporting high numbers of online learners who might lack certain necessary skills. The problems relating to the distribution of a high quality educational service to a mass student body are mirrored by other service institutions. Similar issues have emerged historically in healthcare provision, as national health services have struggled to cope with influxes of patients. Potential solutions and approaches to solve educational problems can, then, be borrowed, to some extent, from the field of healthcare, where the development and compensation of specific skills, alongside a focus on prevention, often empowered with Artificial Intelligence (AI), is considered to be a cost-effective solution. For example, Mobile Health (mHealth) is a branch of medical research that is predominantly focused on public health support using mobile devices and wireless technologies (for more detail, see, for example, Rehg, Murphy and Kumar, 2017). The application of AI in mHealth to design interventions has the potential to offer a widely accessible, evidence-based, personalised and inexpensive solution to treat chronic conditions (Menictas, Rabbi, Klasnja and Murphy, 2019, p. 23). Cross-disciplinary transfer from medical to social science and vice versa is not new. For example, Coe, Fitz-Gibbon and Tymms (2000) have noted that the term 'evidence-based education' was borrowed from 'evidence-based medicine'. Another example is the Randomised Controlled Trial (RCT) research design, emerged from experimental research in education and psychology (Oakley, 1998). The modern approach to RCT emerged from experimental agriculture (Torgerson and Torgerson, 2008, p. 17) and currently RCT research design is utilised in both fields (educational and medical studies). For example, RCTs applied in studies on improving learning (Elliott, 2001; Torgerson and Torgerson, 2001), supporting evidence-based policy in education (Gorard, See and Siddiqui, 2017; Katsipataki and Higgins, 2016), and in studies focusing on eliminating global poverty (Banerjee et al., 2015; Tollefson, 2015). This approach to solving the issue of global poverty was recently recognised with the Nobel Prize in Economics (awarded to Michael Kremer, Abhijit Banerjee, and Esther Duflo). Richard Mayer, an educational psychologist, looked with optimism at the prospect of combining different solutions to educational problems, such as applying indirect assessment together with adaptive interventions:

> Computer-based technology is likely to play a useful role in helping monitor each student's growth in knowledge, analogous to the use of self-monitoring devices in fitness that provide a continuous reading of miles walked, steps climbed, heart rate, and the like. Real-time monitoring of each learner's knowledge, motivation, affect, and metacognition can also help instructors adapt their instruction, so a focus on building feedback that leads to more effective adaptive instruction is an important related goal for the future. (Mayer, 2018, p. 176)

Another critical issue affecting learning at scale is the trend to resurrect behaviourist approaches in education. A recent meta-analysis of educational research published between January 1999 and March 2015 has shown that 40% examined learning outcomes, referred uncritically on behaviourist epistemology, and less than one-tenth made reference to behaviourism during their critical analysis (Murtonen, Gruber and Lehtinen, 2017). This trend has been fuelled by the EdTech industry's attempt to adopt the model of learning at scale as the core of its business model without considering the limitations of the behaviourist tradition and advances in cognitive science (Knox, Williamson and Bayne, 2020; Yeung, 2017). The current trend of the excessive behaviourisation of the learning process and education in general, amplified by technology has been mentioned by Knox, Williamson and Bayne (2020):

> In this way, learning itself is reconceptualised in terms of psychologically quantifiable affective characteristics which are both detectable as autonomic bodily signals and amenable to being changed and modified in line with particular theories about what constitutes the 'correct', 'preferable', or 'desirable' behaviours for learning. Psychologists of grit, growth mindset and character have supplied the intellectual grounding for the advance of behaviour change and nudge programmes in education, inspiring developers of analytics packages and apps to embed behavioural design approaches in their products, and to create emotionally-sensitive and potentially persuasive machine learning systems. (p. 11)

Although this statement ignores the cognitive aspects of knowledge and skill acquisition, one possible answer to the obstacles of learning at scale might lie in the development of specific learners' skills or their compensation using technological solutions such as AI. Moreover, it is vital to select the best practices from a range of perspectives on the ways in which educational practices can respond to the challenges of modern time in the most appropriate way.

1.4 Characteristics of online learning

While considering the skills that may lead to the successful utilisation of opportunities provided by online learning, it is essential to comprehensively examine the learning process and the factors that determine it. This is a challenging task as the broad range of scientific disciplines and research traditions that have analysed these educational questions have a variety of answers to the question of the Holy Grail of the online learning skill-set. In addition to learners' intellectual capacity to process information, some researchers favour a motivational set of skills (Lazowski and Hulleman, 2016), others advocate for metacognitive skills (Azevedo and Aleven, 2013), social participatory (Wenger, 2018), and self-regulatory skills (Schunk and Greene, 2018). Other researchers have pointed out additional contributing factors, e.g. working memory, beliefs, encouragement, the expectations and influences of a learner's cultural background (Hattie and Donoghue, 2018, p. 102).

In order to select a direction for further research, and due to the nature of this work, the three-dimensional framework used in research on complex problem solving (see, for example, Birney, Beckmann and Seah, 2016, Beckmann and Goode, 2017, Beckmann et al., 2017) is applied here. The Person, Task, and Situation framework (PTS) takes into account personal, task-related, and situational variables. The three-dimensional approach allows the learning process to be broken down, with differentiations between a learner, a learning task, and a learning situation — each viewed as independent sources of complexity (Beckmann et al., 2017, p. 1). In this framework, complexity is conceptualised as 'a quality that is determined by the cognitive demands that the characteristics of the task and the situation impose' (p. 1). Complexity is distinguished from the concept of difficulty, which is defined as 'the quantifiable level of a person's success in dealing with such demands' (p. 1). Therefore, the effective utilisation of learning opportunities depends on several dimensions, including the learning task, the learning environment, learner characteristics, and their combinations.

1.4.1 Task

A learning task has two sub-facets: task representation and task as an instruction given to a learner. Both sub-facets contribute to the task's complexity. As mentioned in the framework description, learning tasks vary in complexity and require varying levels of effort from a learner (Beckmann et al., 2017). Given its dual nature, a learning task in online learning environment is first determined by an online course's approach of instructions, for instance, linear instructionalism in case of xMOOCs or a non-hierarchical network-based connectivism in case of cMOOCs. Secondly, complexity depends on a task's specific characteristics, such as the number of items constituting a task, the number of connections between them, and the complexity of interactions between the elements within a task. Each possible combination of task sub-facets options will require different levels of effort from a learner, again expressed in task complexity.

1.4.2 Situation

The effects of learning are influenced by the characteristics of a learning environment. The situation component in the PTS framework refers to the environment in which a learning task is given and performed, such as domain characteristics, and environmental conditions in which instructions are provided. Situational characteristics are an essential component to understanding the effective utilisation of learning opportunities. Previous studies have shown that learning opportunities in micro-worlds (or simulation settings) are not always utilised as intended (Beckmann, Beckmann, Birney and Wood, 2015). Solely focusing on encouraging learners to work collaboratively is not sufficient to enable learners to utilise all the opportunities provided by the environment. Research has confirmed that an integrated approach for communicating expectations, explicating assumptions and justifying decisions has methodological potential in attempting to solve this issue. Despite different situational settings and their unique characteristics, situations can be conceptualised and categorised, measured and reported with the help of taxonomies by framing them along with each other (Beckmann and Wood, 2017). For taxonomies to report on situational characteristics see, for example, works conducted by Parrigon, Woo, Tay and Wang (2017); Rauthmann et al. (2014); Rauthmann and Sherman (2016).

It is worth adding that advances in technology contribute to the variety of situational characteristics that are available for consideration. For example, the decisions made in terms of the technological solutions used to communicate a task to a learner may have learning consequences. The same task can be presented on a computer screen with different resolutions, or it could incorporate recent advances in technology, such as Virtual Reality (VR) and Augmented Reality (AR) options.

Taking into account situational characteristics is especially important in online learning settings as these environments are characterised by the presence of distractions that are irrelevant and even detrimental to learning. Such disturbances may result in behavioural shifts, with, correspondingly, an excessive demand on mental resources in order to resist such shifts (Mayer, 2018). Therefore, task and situational characteristics contribute to the complexity experienced by a learner (Beckmann et al., 2017).

1.4.3 Learner

The Person dimension of the PTS framework focuses on learners' individual differences, such as specific cognitive processes relating to cognitive control, including problem-solving, cognitive flexibility, the ability to sustain attention, to maintain a selected path while performing a task, to switch between tasks, and to deal with novelty. Learners' personality traits (e.g. conscientiousness, neuroticism), relevant experience, and skills are also involved in one's performance in solving complex and dynamic real-world problems (Wood, Beckmann and Birney, 2009). In addition to the the most commonly reported personality traits, personal characteristics such as self-esteem, subjective well-being, positive personality development, perceived control, goals and motivation, attachment style, identity formation, and personal narratives (Specht, 2017, p. 5) are all examples of latent traits that can determine a learner's performance. Taken together, observed performance expressed in performed behaviour is the result of the difficulty a learner experiences, given personal, task and situational characteristics. As was noted in the description of the PTS framework (Beckmann and Goode, 2017), difficulty is the observable reflection of complexity.

In the context of online learning, students may experience additional and unexpected difficulties due to the democratised enrolment process. For example, some online courses are freely available for enrolment with recommended, but not mandatory prerequisites. This is in contrast to their on-campus counterparts, which require rigorous prior assessment: e.g. obtaining certain scores in commonly used tests, such as the International English Language Testing System (IELTS) or the Graduate Management Admission Test (GMAT). As a result, online learners may skip prerequisite requirements, enrolling on courses that require the allocation of additional mental resources to compensate for an unexpected demand for language fluency or particular skills required for mastering the course materials offered online.

Students with certain characteristics may be able to extract additional benefits from online learning. With the wide availability of educational resources, it is crucial to not only to have access to learning materials, but to also have the ability to evaluate and select the right resources for further learning. With the ever-increasing rate of knowledge obsolescence (i.e. the half-life of knowledge), the flexibility of switching between different resources (i.e. shifting) and removing resources that have lost their relevance are all of benefit to learners. Thus, learners with certain traits (e.g. openness to experience) might experience an increased benefit from online learning environments. Therefore, learners' skills and the characteristics conducive to acquiring and maintaining skills, are necessary companions to successful learning in the 21st century.

1.5 Lifelong learning and digital citizenship

Continuous learning over a lifetime is not unique to the internet age. There have been several historical periods when societies have experienced significant changes that have brought with them the requirement for many professionals to master new competencies or to change their occupations, e.g. development of mechanised labour, continued with waves of industrial and information revolutions. Discoveries in research on education beyond adolescents have led to the development of adult learning theory, Andragogy. This theory was first proposed by Malcolm Knowles (1978) in the 1960s. Andragogy has unique features, distinguishing it from other pedagogic concepts through its focus on adult learners, with a particular emphasis on motivation, problem-based, and self-directed learning approaches. Knowles' effort progressed to the further exploration of adult education and resulted in Self-directed (Tough, 1971) and Transformative (Mezirow, 2018) learning theories, which first appeared in the 1970s. Although critiques of andragogy have appeared in recent years (Henschke, 2011), it is evident that adult learning is distinguishable from other pedagogic approaches in terms of two further features attributed to adult learners:

self-directedness and self-reflection (Birney, Beckmann and Wood, 2012). Overall, debates around the dominance of adult learning theories over pedagogical ideas in adult learning have led to the recognition that continuous learning over a lifetime is reshaping learning needs significantly, and playing a crucial role beyond merely accounting for a learner's age and corresponding stage of development. Further focus on the learning process, fuelled by advances in educational psychology (e.g. works on situated cognition), have led to a more holistic concept of learning (Merriam, 2017). As remarked by Biesta (2013), due to 'learnification' of education, the focus of today's research agenda has shifted from adult education to lifelong learning.

Lifelong learning is a broad concept that is predominantly referred to in cognitivist, constructivist and connectivist learning theories. Lifelong learning requires certain skills to continuously and persistently engage with education as new knowledge arises and old ideas are revised. Lifelong learners need to successfully apply learning transfer, self-direction, and self-regulation. Norman Longworth (2019) advocates for lifelong learning as an agent for change and highlights its focus on the learning process, the needs and requirement of learners, with a holistic and proactive philosophy at its core, incorporating economic, social, cultural and educational differences. Examination and assessment methods, according to Longworth, in lifelong learning are utilised to indicate progress and promote further learning, and even forming the habit of learning, rather than indicating success or failure.

Ideas embedded in lifelong learning have prompted a period of reorganisation within the education system (Alheit, 2018) and have led to a broader interpretation of its societal impact, resulting in the impetus to teach digital citizenship. Digital citizenship is understood as an extension to basic assumptions of citizenship that have arisen with the digital century. Digital citizenship includes students' readiness to deal with novelty, make continuous developments, communicate effectively across different media means, think critically, and act appropriately and responsibly in digital environments (Choi, 2016). Digital citizenship has become an integral part of education, and some researchers are raising provocative debates around its impact on the future datafied society. Choi (2016) stresses the importance of digital citizenship as a primary goal of education, while other researchers are pushing current trends in education towards ‘radical digital citizenship’ (Emejulu and McGregor, 2019), and ‘postdigital’ education (Knox, 2019). As an example of these debates, Macgilchrist, Allert and Bruch (2020) proposed a scenario that is likely to appear in the near future as a possible outcome of continuing the current policy, where:

> [S]tudents are encouraged by policymakers, schools and universities to use new technological tools efficiently to increase their productivity. Students are addressed as individuals who optimise themselves; they monitor, adjust and curate polished lives that fit a frictionless high-tech world. When technology is understood as a ‘tool’ to be used competently, post-democratic moves are strengthened in which governments invite technology corporations to advise them on their educational technology strategy. As promised, technology helps close the ‘achievement gap’, but observers are puzzled when socio-economic equality is still not achieved. With decision-makers foreground technical solutions, the few critical voices noting that addressing inequality takes more substantial (and conflictual) transformation are marginalised. (Macgilchrist, Allert and Bruch, 2020, p. 10)

1.6 Online learning, self-regulation, and individual differences

Online learning and MOOCs provide new opportunities to spread education globally. However, inequality in the online learning environment still exists. These inequalities are expressed in the different outcomes obtained from online learning depending on race, sex, income, prior education, culture, or country of origin. For example, learners from developed countries benefit more than those from less developed countries (Kizilcec et al., 2017). Representatives of certain cultures, backgrounds and individual contexts have different learning behaviours, resulting in online learning being more advantageous for some than others (Hood, Littlejohn and Milligan, 2015). Therefore, learners differ, and their individual differences contribute to success or failure in online learning, and refer to the Person in the three-dimensional Person-Task-Situation framework.

Demand for lifelong learning and changes during a learner's lifespan, including stages of development, decline, affect learning and involvement in education. The specific characteristics of online learning, such as the variability of educational resources and learning tasks, involvement in unfamiliar learning environments and multicultural study groups, and lack of support all require learners to allocate additional cognitive resources, be persistent, and rely on self-direction and self-motivation (Hood et al., 2015). These requirements bring many challenges for learners. For example, among the multifarious possible problems, the issue of unwillingness and the fear of acquiring new knowledge, difficulties in self-regulation and following set goals, poor communication with others, experiencing anxiety and maladaptive thoughts, involvement in addictive behaviour, and the problem of compliance. The situational characteristics of online learning demand learners' self-regulatory skills. At the same time, online learning provides opportunities to relieve these burdens by mastering new skills, improving attention, recognising and controlling emotions, effectively applying self-regulatory and metacognitive strategies, distributing cognitive abilities efficiently, and exercising self-control. In addition to intentionally developing skills, learners could learn to compensate for required skills in certain circumstances.

Without underestimating other aspects, the primary focus of this thesis is on the learner. Online learning tends to require higher levels of self-regulation than traditional classroom-based learning, and some online learners might not have sufficient resources (e.g. degree of autonomy and self-regulatory proficiency) to meet this need. This can be explained with attention to three dimensions provided in the Person-Task-Situation framework: first, the characteristics of online learning environments that may contribute to the failure of self-regulatory behaviour, second, the educational content provided in online courses, and finally learners' individual differences. All of these factors may make it more challenging for students to allocate their resources to a learning task, therefore, increasing the perceived task difficulty. Lack of self-regulation can affect learners' engagement with the course content, resulting in sub-optimal learning outcomes or failure to complete a chosen course.

Self-regulation (as a learner characteristic) in this context is one of many other possible factors that may influence learning. It is assumed that self-regulation is a skill that can be acquired, developed, and compensated for to help online students to learn in the context of online learning. Self-regulatory skills are considered to be a desirable option for further exploration, with the aim to help online learners better utilise the opportunities opened up by online learning.

The central idea behind this doctoral research project is to gain a better understanding of how online learners can more effectively utilise the opportunities provided by online learning. To achieve this aim, the present research involves conceptualisation, operationalisation and prescription phases in order to develop and compensate for self-regulation in online learning. In the context of this research, developmental changes assume skill acquisition, and compensatory changes are understood as behavioural changes (i.e. changes acquired without skill acquisition). This sequence is phased across several main steps: i) conceptualisation of self-regulation; ii) operationalisation of self-regulation iii) selection and prioritisation of intervention content for inclusion, in order to develop and compensate self-regulation among online learners; iv) collection of self-report and trace data on online learners' behaviours, as well as observations, classifications and explanations for any possible discovered behaviour patterns and individual differences; v) analysis of relationships between behavioural measures and scores obtained from questionnaires regarding self-regulation and individual differences; vi) analysis of collected trace data and identified patterns to report on effects of the intervention. These steps are outlined in the chapters that follow.

2 | Conceptualisation of Self-Regulation

This chapter investigates the conceptualisation of learners' self-regulation. It aims to provide a description of the phenomenon, exploring how self-regulation relates to the major frameworks of thinking processes involved in learning, individual differences and proposed models of self-regulation in learning. The theoretical focus of this chapter aims to explore to what extent improved self-regulation might be a solution to the more effective utilisation of learning opportunities and how to deal with the challenges associated with online learning. To achieve this aim, first, a detailed description of the psychological frameworks associated with the thought processes involved in learning is provided. Second, individual differences and changes in learners' self-regulatory skills over a lifespan are described. This conceptualisation flow should give a theoretical foundation for furthering an understanding of components involved in self-regulation and their interactions.

2.1 Theoretical foundation

2.1.1 Vygotsky's functional learning systems

The first theory in this section, focused on theoretical frameworks for thinking, is drawn from the work of Lev Vygotsky. A key principle of Vygotsky's work is the idea that learning does not occur in isolation, and, moreover, that it is beneficial for learners to engage in social interactions and learn in social environments, which benefit their cognitive development. A less proficient learner, Vygotsky (1978) adds, should also be guided by a more advanced and knowledgeable person in order to achieve the best possible outcome. Vygotsky advocates for the sociogenesis of intelligence, arguing that biological limitations can partly be mitigated by the support of culture. According to Vygotsky, a learner's cognitive functions are developed under the influence of cultural aspects (Vygotsky, 1978):

culture serves as a tool of intellectual adaption and is acquired by a learner. The connectivist learning approach (Siemens, 2005) resonates with this aspect of Vygotsky's theory, wherein certain cognitive functions can be extended and enhanced with an external medium. Culture can serve as such medium.

In the age of Google, the learning culture is characterised by reliance on external tools such as search engines and Wikipedia to enhance memory (for more details, see the work of Risko and Gilbert (2016), and Hu, Luo and Fleming (2019) on cognitive offloading). Cognitive functions involved in learning can be enhanced with the help of external assistance from digital tools. Of particular interest here is the concept of the Zone of Proximal Development (ZPD) (Vygotsky, 1978). Vygotsky's ZPD outlines the ways in which the functional learning system and its associated skills are developed during early years, enabling estimates of what might be possible for the developed learner, and what might be challenging and beyond the abilities of the learner at a lower stage:

> The ZPD can therefore be seen [...] as a sphere formed by the aggregate of vectors that pass through a "point" of difficulty and that delineate a child's diverse possible areas of development (the zones of potential personality and cognitive changes, among others). (Zaretskii, 2009, p. 86)

Wood and colleagues extended Vygotsky's ZPD with the idea of scaffolding (Wood, Bruner and Ross, 1976). According to Wood's model, it is assumed that in order to help a learner to complete a task, external support must be provided. The learner is given initial assistance to complete the task, but the level of support is decreased over time. This allows the gradual development of the learner's level of competence, until, at a certain point, no assistance is needed (Guile and Young, 1998). Learning is facilitated through the use of external resources. The idea of scaffolding has direct implications for self-regulation, due to beneficial effects of scaffolding on learners' cognitive abilities (Hammond, Müller, Carpendale, Bibok and Liebermann-Finestone, 2012; Quintana, Zhang and Krajcik, 2005). In addition, Vygotsky's highly influential ideas on the importance of social interactions to the development of higher cognitive processes have had a profound effect on research of a number of other theories and frameworks, in particular, Wallace and Adams' 'Thinking Actively in a Social Context' (TASC) framework (Moseley et al., 2005, p. 264), which explores scaffold learning and problem solving.

Criticisms of Vygotsky's works centre around identifying a starting point for scaffolding in Vygotskian ZPD and inconsistency in used terminology (often due to available translations). ZPD seem to contradict Piaget's stage model of cognitive development (described in the subsection below) suggesting that, for example, a child may participate in an advanced activity with a more experienced learning partner for which the child is not ready (Matusov and Hayes, 2000, p. 219). However, it is difficult to apply this idea to online learning, as learners in this context tend to be predominantly adults (Ho et al., 2014; Li, 2019). In contrast to Piaget's focus on the involvement of the discovery process in an individual's development, Vygotsky stressed the role of meditation as the intermediate layer through which culture and institutions might influence one's development (Matusov and Hayes, 2000, pp. 221-222). However, it can on occasion be challenging for teachers to identify the right level of a learner's development so that suitable scaffolding can be provided (Howe and Abedin, 2013, p. 342; Silcock, 2013, p. 317; see also what Grigorenko, 1998 called 'starting points'). This has direct implications for online courses at scale, such as MOOCs, as providing computer-generated scaffolding without human expertise may make it more challenging to establish such 'starting points'. Potential solutions to overcome this issue can be found in works on knowledge component decomposition (Koedinger, Booth and Klahr, 2013) and dynamic assessment (Beckmann and Guthke, 1995; Elliott et al., 2018).

Further criticisms of Vygotsky's ideas such as the 'internalisation', 'joint construction', 'language mediation' and educational acculturation have been summarised by Silcock (2013). However, the most notable critic of Vygotsky's works is Vygotsky himself. An analysis of Vygotsky's private notes and correspondence conducted by van der Veer and Yasnitsky (2015) reveals Vygorsky's critical attitude to his early works (van der Veer and Yasnitsky, 2015, p. 85). For example, after 1929 Vygotsky began to question some of his 'foundational concepts and terms that he had been using until 1929 were no longer satisfactory and valid', as in the case of the term 'psychological function' (p. 85). Perhaps as a result of his dissatisfaction and critical self-reflection, the later years of his work contributed to re-conceptualisations that led to fruitful discoveries (p. 86). Vygotsky's works, for instance, had a significant impact on Jerome Bruner's work (Bruner, 1986; Silcock, 2013, p. 318), whose discoveries greatly contributed to the field of instructional design and the design of online learning environments (see, for example, Bruner, 1966, 1977).

2.1.2 Piaget's stage model of cognitive development

Jean Piaget proposed the concept of learning as discovery; a learner can, according to this model, effectively discover solutions by applying different approaches and ideas drawn from past experience. Piaget argued that development must precede children's learning, and, in contrast to Vygotskian ZPD, suggested that a single principle of development (achieving equilibration through the utilisation of schema) is responsible for learning (Piaget, 1952). Piaget distinguished four main developmental stages: sensorimotor (since birth up to 2 years old), preoperational (2 to 7 years old), concrete operational (7 to 11 years old), and the formal operational stage (12 years and older). Learners, regardless of their cultural background, must pass these stages sequentially to develop the foundations which are prerequisite for learning (Moseley et al., 2005, pp. 190-191).

Critiques of Piaget's works have clustered around several topics. First, Piaget's research was primarily focused on logic and mathematical thinking, ignoring the importance of art and creative disciplines. Secondly, Piaget's stage model of cognitive development includes some overlap between stages. Piaget detailed strict age differentiations in a child's ability to perform certain tasks, which is contradicted by research findings that indicate that children can perform the specified tasks at an earlier age. The importance of language abilities and social context to determining the full potential of a child's development has also been questioned, as language is only one of a range of factors that cause developmental differences (Moseley et al., 2005, pp. 193-194).

Piaget's ideas have had a profound influence on pedagogy, cognitive psychology and information processing theory, and have been yet further developed by representatives of the neo-Piagetian perspective (for an overview of the neo-Piagetian perspective, see, for example, a collection of works edited by Demetriou, Shayer and Efklides (1992)). The work of Piaget and his followers have significantly contributed to a shift in the understanding of different developmental stages, resulting in more detailed understandings of cognition, the emergence of the theory of 'representational redescription' (a conceptualisation of the mental processes responsible for producing a new understanding of a child's existing representations) and allowing for a more dynamic and complex understanding of human development (Martí, 2018).

2.1.3 Carroll's three-stratum theory of cognitive abilities

A key contribution of Carroll's three-stratum theory of cognitive abilities is that it created a hierarchy delineating three levels of generality of abilities, detailing each corresponding level. Carroll's theory resulted from a large factor analysis applied to learners' performance data. This model assumes that 'success in learning will very often depend to a certain extent on general intelligence and a lesser extent on broad abilities' (Moseley et al., 2005, p. 223). With respect to the generality of factors over the total domain, Carroll distinguished three levels of abilities: narrow, broad, and general. The narrow scope of abilities is represented by 50 to 60 plus abilities, when the so-called broad range of abilities consists of 8 to 10 abilities, and finally, the general level of ability is represented by only a single, general factor (Carroll, 2003, p. 3).

In his search to identify a general predictor of future success, Carroll defined 'achievement' as 'the degree of learning in some procedure intended to produce learning, such as a formal or informal course of instruction, or a period of self-study of a topic, or practice of a skill' (Carroll, 1993, p. 17). This definition reflects his understanding of cognitive tests as measures of achievement as a predictor of future performance. One of the core components of this composition (provided in the definition) is its focus on the learners' ability to self-regulate. Carroll's research on the three-stratum theory of cognitive abilities provide hope that certain abilities can be developed through education, particularly those abilities which can influence learners' self-regulation.

2.1.4 Feuerstein's theory of structural cognitive modifiability

Combining Vygotsky's ideas about socially and culturally mediated learning with Piaget's cognitive structure and function, Feuerstein was one of the first to pioneer instructional design. Feuerstein's position states that in the teacher-mediated approach, knowledge and meaning are constructed by learners (Moseley et al., 2005, p. 45). For an individual to become an independent learner Mediated Learning Experience (MLE) is a crucial factor, as it helps to create the supporting conditions necessary for successful learning. MLE can be defined as a structured approach to learning with a mediated agent that controls and provides a suitable stimulus to a learner (Moseley et al., 2005, pp. 55-56):

> Mediated learning experience provides the organism with modalities of functioning that will enable him or her to make use of stimuli and learning events for the construction and elaboration of progressively new schemata under the specified conditions of direct of cognitive functions, as well as for the formation of new and more elaborate need systems. In this way, cognitive growth is enhanced along with autonomous and self-regulative transformation of cognitive schemata leading to creativity and plasticity. (Feuerstein and Jensen, 1980, pp. 410-411)

Based on Feuerstein's theory of cognitive modifiability, the intervention program Instrumental Enrichment (IE) (a series of paper-and-pencil tasks) was introduced to support the development of learners' cognitive skills (Blagg, 2012). Feuerstein advocated for the idea of cognitive modifiability, whereby learners' are teachable through IE to generalisable cognitive skills. However, for some advanced learners, pre-selected stimuli may cause limitations to the development of learner autonomy. (Moseley et al., 2005, pp. 60-61)

2.1.5 Vermunt and Verloop's categorisations of learning activities

Research on the regulation of constructive learning processes (Vermunt, 1998) and an attempt to categorise involvement in learning has led to the three-level categorisation of learning activities (Vermunt and Verloop, 1999). This categorisation includes cognitive, affective and regulative (metacognitive) activities (Vermunt and Verloop, 1999). The proposed categorisation of learning activities locates learners' and teachers' regulation practices at the centre of learning. While of great importance to research in education more generally, this framework has had immense value for studies relating to higher education, and more specifically, adult learning (Moseley et al., 2005, p. 281).

In addition, Vermunt and Verloop referred to learning styles in their categorisation. It is worth noting, however, that the theory of learning styles has recently been debunked. The research community has increasingly treated this formula with scepticism as available evidence from several studies (An and Carr, 2017; Kirschner, 2017; Pashler, McDaniel, Rohrer and Bjork, 2008) disproved theories of learning styles in favour of accounting for individual differences in learning, rather than pre-specified styles.

2.1.6 Sternberg's model of abilities as developing expertise

Robert Sternberg, one of the most notable theorists to describe cognitive abilities, proposed the model of abilities as developing expertise. According to Sternberg's model, for an individual to develop expertise relies on the interaction of several elements: metacognitive skills, learning skills, thinking skills, declarative and procedural knowledge, motivation, and context (Sternberg, 2001).

Effective utilisation of intelligence, according to Sternberg, involves the ability to achieve success. This ability depends on capitalising on one's strengths and correcting or compensating for one's weaknesses (Sternberg, 1984, p. 272). Sternberg raised the idea that education should not only aim to develop a learner's abilities but should incorporate the development of skills to compensate or correct for a learner's weaknesses. Sternberg developed this idea further in his work on the triarchic theory of intelligence (Sternberg, 1986). Sternberg's model of abilities as developing expertise, together with his triarchic theory of intelligence serves as a basis for designing educational interventions. Effective applicability of this approach supported with evidence from research findings in several domains, including curricular interventions with the triarchic model as their basis (Moseley et al., 2005, p. 294).

2.1.7 Bandura's theory of self-efficacy

Albert Bandura is known for his work on the social learning theory (Bandura, 1971). In accordance with Vygotsky, Bandura acknowledged the importance of social interactions, considering these to be at the heart of a child's development. Bandura developed key theories through several important studies that resulted in transformative changes in principles associated with the social learning theory and led to the development of the social cognitive theory. Bandura proposed his social cognitive theory of self-regulation (Bandura, 1991), a representative of socio-cognitive theories. One of the main components of Bandura's social cognitive theory is a self-regulative mechanism which operates through three functions: self-monitoring one's behaviour, the evaluation of performed behaviour according to some standards (e.g., settled by a social group), and affective self-reaction (Bandura, 1991, p. 248). The self-efficacy mechanism lies at the core of the social cognitive theory, and, as mentioned by Bandura, it 'plays a central role in the exercise of personal agency by its strong impact on thought, affect, motivation, and action' (Bandura, 1991, p. 248). Further, in his theory of self-efficacy Bandura highlighted the role of social models and perceived experience on a learner's development.

Bandura defined self-efficacy as 'people's beliefs in their capabilities to exercise control over their functioning and over events that affect their lives' (Bandura, 1994, p. 14). According to Bandura, beliefs in personal efficacy have long-term outcomes over the course of an individual's life. It affects one's motivation, performance, control over distractions, and the capability to cope with stress. Self-efficacy has four primary sources of influence. First, self-efficacy can be developed through experience of mastering tasks. Experiencing success reinforces one's belief in his or her personal efficacy. Failures act negatively, especially if the sense of efficacy had not been firmly established. Second and third sources include the influence of social interactions. In the main, self-efficacy is formed and strengthened through experience with an orientation provided by social models. Social persuasion also plays a role in strengthening the belief that it is possible to succeed in the task at hand. The fourth source of self-efficacy is the reduction of exposure to stressful and harmful events, such as reducing negative affect. To summarise, self-efficacy plays a crucial role in one's motivation, behaviour and affect. Self-efficacy, as a learner's characteristic, is developed and changed during a lifespan. Four groups of processes activate self-efficacy: cognitive, motivational, affective, and selection processes (Bandura, 1994).

2.1.8 Comparability of theoretical foundations with the characteristics of online learning

To conclude this section, a short overview of the considered theoretical constructs is provided. Bandura's ideas regarding the modifiability of aspects of self-regulation are in line with Carroll's and Feuerstein's work. According to Carroll's three-stratum theory, low-level abilities influence an individual's self-regulation, and these abilities can be developed. According to the idea of cognitive modifiability proposed by Feuerstein in his approach to learning known as mediated learning experience, special interventions can be applied to develop learners' cognitive skills, such as an external agent that provides learning stimuli. In accordance with Feuerstein's instrumental enrichment, cognitive skills are teachable, and self-regulation as a cognitive skill can be taught. Thus, learners can improve their self-regulatory skill-set with suitable guidance.

This idea of self-regulatory development can be extended further. The assumption of Vygotsky's zone of proximal development and its related concept of 'scaffolding' is that cognitive development can occur if a learner initially receives external support which is gradually decreased over time. This scaffolding mechanism has the potential to be utilised to help learners to develop their self-regulation. This development should occur through a process of building from one level to another, as for Piaget, the sequential nature of development cannot be ignored. This process is, Piaget adds, underpinned by the learner's continued reflection on their experience.

Practical experience, with all of its variations and nuances, is presented in Vermunt and Verloop's works. Vermunt and Verloop identified three categories of learning activities: cognitive, affective and regulative. Learners' regulatory practices are at the core of learning, especially in higher education and adult learning. More specifically, as mentioned by Sternberg, the effective utilisation of cognitive resources requires reliance on one's strengths and the ability to compensate for one's weaknesses. It involves metacognitive learning, thinking skills, motivation, declarative and procedural knowledge. The role of education, according to Sternberg, is not only to help learners to develop cognitive skills, but to give them the internal instruments to compensate for their weaknesses by utilising other available resources.

The theoretical foundation covered in this section includes theories, frameworks, and models that have been rigorously tested over time. These foundational works indicate that self-regulation is essential to the learning process. The role of self-regulation and its importance is seen to vary from theory to theory; while some theorists pay a little attention to it, others place self-regulation at the core of the learning process. Either way, self-regulation has been shown to be an essential skill for every learner, and one which, crucially, can be developed and compensated for.

2.2 Individual differences and learning

Each learner has a set of unique characteristics that influence their learning performance. These unique characteristics represent a learner in the learning process and interact with a learning task and a learning environment (as noted in Section 1.4). The overview of individual differences provided in this section includes aspects which might affect learners' performance: cognitive abilities, personality traits, self-regulation and context-specific factors. The causality of these characteristics vary and based on a genetic preposition and formed through the influence of the surrounding environment, and learners' efforts to develop a particular characteristic. For example, similarly to the ways in which an athlete's explosive strength and muscle speed are the result of a combination of genetics, diet and training, learners have different information processing speeds for different tasks (e.g. reaction time or differences in noticing and reacting to stimuli). Therefore, learners are different in many aspects, and the aim of the following sub-sections is to highlight the main individual characteristics that have an impact on the learning process.

2.2.1 Cognitive abilities

Cognitive abilities can be broadly describes as several processes responsible for learners' inhibitory control, Working Memory (WM), and mental flexibility (Best and Miller, 2010). Cognitive abilities are expressed by a number of aspects related to learning, such as goal setting, goal-directed behaviour and behaviour management, persistence in acquiring new knowledge, monitoring progress towards a set goal, and responses to external stimuli — for example, reaction to an unexpected distraction (i.e. an immediate response or a delay) (Diamond, 2013).

The first milestone in distinguishing individuals according to their cognitive abilities was achieved through the development of Intelligence Quotient (IQ) tests. Although there have been several cases in which these early tests were inappropriately used, misused, or even abused (see, for example, the case of using IQ tests to control immigration, as described in Mackintosh, 2011, pp. 23-24), it has nonetheless proved to be, to a certain extent, a reliable instrument for the comparison of intellectual abilities at the population level. In addition to the view that cognitive abilities can be represented as a single general factor g, previous research has presented a number of different views on cognitive abilities and how it might be conceptualised and operationalised, including, that cognitive abilities is comprised of a combination of factors proposed in the triarchic theory of intelligence (critical, creative, and practical) by Sternberg (1984), the model of emotional intelligence (Brackett, Rivers and Salovey, 2011), Carroll's three stratum theory (Carroll, 2003), and the synthesised Cattell–Horn–Carroll theory of intelligence (CHC theory) (for description, see, for example, Schneider and McGrew, 2018). These theories are concerned with individual differences in cognitive abilities and how such differences affect general and specific aspects of performance in learning, work-related tasks, and overall life outcomes.

As the contemporary view on intelligence was gradually formed, debates on cognitive abilities shifted to the search for the cognitive processes underlying intelligence and factors responsible for speed and efficiency of information processing. Gustafsson's application of structural equation models has provided further evidence to support the existence of the general factor g, as well as support for Gf (fluid intelligence) and Gc (crystallised intelligence) factors (Carroll, 2003,

p. 4). Behaviour as an indicator of performance in information processing, crystallised (Gc), spatial (Gv) and fluid (Gf) abilities have attracted the attention of researchers, putting the standard multifactorial view on research in cognitive abilities on the agenda (Carroll, 2003). Based on a conducted analysis of evidence, Carroll has supported the standard multifactorial view of cognitive abilities and the existence of fluid and crystallised intelligence (Carroll, 2003, p. 5). This investigation was made possible due to advances in factor-analytical methodology, and the widespread applicability of explanatory and confirmatory factor analyses. These discoveries have led to the contemporary conceptualisation of intelligence, which includes several non-cognitive factors that influence overall performance (Birney, Beckmann, Beckmann and Double, 2017, p. 63), alongside the CHC theory-based model. However, this is likely not the final point in debates on cognitive abilities: advances in research could continue to shape attitudes to cognitive abilities. As Carroll has stated:

> Further research is needed on the best tests and procedures to use in estimating scores on all higher-stratum factors of cognitive ability, and continued psychological and even philosophical examination of the nature of factor g is a must. (Carroll, 2003, p. 17)

When IQ tests first began to appear as the dominant method of measuring and identifying differences in cognitive abilities Raven's matrices were used (Mackintosh, 2011). With the help of information technology, novel implementation of tests and the computerised assessment of intellectual abilities has lead to important discoveries in research on cognitive abilities. For example, additional factors such as an intermediate layer between the second and third strata of the CHC theory-based model have been identified in the revised version of the Woodcock-Johnson Tests of Cognitive Abilities (Taub and McGrew, 2014). Still, neuropsychologists and psychometricians have disagreed over which might be the most appropriate measure for assessing differences in cognitive abilities: executive tasks or traditional IQ tests (Mackintosh, 2011, p. 125). Advances in technologies, coupled with the demand to assess not only the individual's current level of knowledge but their potential for future learning has lead to the development and application of dynamic assessment. The dynamic assessment method was developed in response to the limitations of traditional intelligence tests to capture true ability to learn — such tests are focused on assessing the ability to acquire new knowledge rather than previously formed knowledge (Guthke and Beckmann, 2000; for more general discussion see Poehner, 2008). A number of examples for the application of the dynamic assessment method can be found in Guthke and Beckmann's study (2000), where prompts are arranged to appear on-screen for learners in need of assistance; the number of times these prompts are requested was utilised to estimate the individual's true learning potential level (the learning test concept). Similarly, the frequency of the need for self-regulatory assistance, indicated by learners' behaviour, could have the potential to be utilised to estimate learners' levels in self-regulation. Furthermore, it has been shown empirically that differences in performance in cognitive tasks depends on self-regulatory processes (Birney et al., 2017). Thus, despite different views on cognitive abilities and its assessment processes, self-regulation has an enabler or facilitator role in translating cognitive abilities (e.g. working memory, information processing capacity) into observable behaviour that is evaluated as performance in tests of cognitive abilities.

2.2.2 Personality traits

Personality traits can be defined as 'differences among individuals in a typical tendency to behave, think, or feel in some conceptually related ways, across a variety of relevant situations and across some fairly long period of time' (Ashton, 2018, p. 29). Research on personality traits has historically been rooted in the research on individual differences. There are a number of different views on the nature of personality traits and their function; some researchers focus on its genetic basis, arguing that human personality serves an evolutionary function, while other perspectives value environmental impact on the development of personality (for more details see Kandler and Zapko-Willmes's discussion (2017)). The idea of the biological basis of personality is supported by theories developed by Eysenck (1970), Cloninger (1987), and Gray (1987). However, empirical evidence has shown mixed results regarding the impact of biological basis in personality development. As a result of this mixed evidence, the majority of researches have taken a pragmatic view, locating their position between these extreme poles, and advocate for a consensual model in personality psychology (see, for example, Kreitler, 2019), which poses the risk of distortion of the phenomenon in question.

Several attempts have been made to find a reliable and valid measure to locate and describe differences in personality, including Jackson's Basic Personality Inventory, Morey's Personality Assessment Inventory, the NEO test (abbreviated from neuroticism (N), extraversion (E), and openness to experience (O), but also includes agreeableness and conscientiousness), and the Personality Inventory framework (Costa and McCrae, 1992). Research attempting to extract factors that might be associated with personality was originally based on lexical studies, where the language used to describe a person was analysed. In this approach, as in the case of Carroll's three-stratum theory of cognitive ability, the application of the factor analysis played a crucial role.

The importance of personality in shaping life outcomes and even the ways in which an individual might navigate everyday situations have been acknowledged through the emergence of the cognitive-affective system theory of personality. This theory emerged through a series of experiments conducted by Walter Mischel and Yuichi Shoda (1995). In their work, the authors proposed a shift from understanding personality as a set of disparate person variables to cognitive-affective units. Mischel and Shoda suggested that personality traits affect behaviour not as a single factor, but as traits which are dependent on situational characteristics and experienced self-perception. These units were included in the personality mediating system and consisted of encoding, expectancies and beliefs, affects, goals and values, competencies and self-regulatory plans (Mischel and Shoda, 1995, p. 253). Attempts to establish a structure of personality traits for convenience in assessment have resulted in the five-factor model of personality traits, commonly known as the Big Five model of factors (agreeableness, conscientiousness, extraversion, neuroticism and openness to experience). Among proposed models of personality traits is the HEXACO Model (Lee and Ashton, 2004). This model is unique in that it contains additional factors beyond the scope of the Big Five model as, it has been suggested, not all personality traits can be associated with the Big Five factors. For example, egotism and manipulativeness can be associated with the HEXACO model of personality characteristics (Gaughan, Miller and Lynam, 2012).

An individual's personality influences life outcomes, and each dimension of personality has its advantages and disadvantages to daily life. Personality traits correlate with abilities and skills, for example, a personality trait such as extraversion might have a significant impact on communication skills. Individuals with high levels on the Honesty-Humility and Agreeableness scales might benefit from a greater degree of cooperation, in comparison to others. Similarly, high levels of extraversion, conscientiousness and openness to experience might lead to social or material advantages from being involved in social and task-related initiatives.

Traditionally, personality traits are considered as a stable construct, which can be utilised to explain some aspects of human behaviour and cognitive task performance (Beckmann, Beckmann, Minbashian and Birney, 2013, p. 447). Despite being relatively stable in adulthood, personality traits vary in childhood and adolescence, with some specific personality characteristics developed in adolescence and young adulthood, e.g. through socialisation (Harris, 2000) and interactions with peers (Reitz, Zimmermann, Hutteman, Specht and Neyer, 2014). Recent research on personality variability within and across contexts has bolstered evidence for the conceptualisation of personality as a dynamic construct, which is context and source depended, varying systematically according to context (Beckmann et al., 2020). The Five-Factor Theory (FFT) perspective of personality assumes that the basic tendencies of personality traits are decontextualised (Mõttus, 2017, p. 94). Context-specific factors can influence personality differences and development, however, this influence only occurs at the level of characteristic adaptations and not at the level of basic tendencies. This nuance distinguishes FFT from the Big Five personality traits theory, where it is assumed that the environment can influence both classes of personality constructs (Mõttus, 2017, p. 95). It is also worth noting that people with different personalities place themselves in different environments. This relationship is called the person-environment transaction (Caspi and Roberts, 2001), and this factor should also be taken into account when evaluating the effect of personality on development and the role of personality on life outcomes.

Personality traits, such as those that facilitate communication skills, are undoubtedly important in shaping general life outcomes as well as learning. However, intellectual abilities can easily be considered crucial to learning. For example, in young and elderly adults, visuospatial abilities and inclinations are correlated with high scores in conscientiousness and emotional stability (i.e. low scores in Neuroticism) (Carbone, Meneghetti and Borella, 2019). Research on the relationship between personality traits and cognitive abilities demonstrates that individual differences in personality are important for interpreting general intellectual performance. In particular, Openness and Conscientiousness are related to the general factor of intelligence (g) (Osmon et al., 2018). Projecting these insights onto to the context of online learning, it is expected that scores in conscientiousness, analytic thinking, and openness to experience are associated with successful online learning, particularly in outcomes related to scores in multiple-choice quizzes and final grades (Abe, 2020). However, the reported relationship between cognitive abilities and personality traits might be questioned: it is common practice in contemporary research to not separate the variance caused by general and narrow cognitive abilities in reporting results of conducted studies (Reeve, Meyer and Bonaccio, 2006). Correct interpretation of research findings can be further complicated by task-situational characteristics (Birney et al., 2016) such that some personality traits have a performance facilitating effect and may influence the learning process. For example, neuroticism in certain situations is associated with a positive effect on cognitive performance (Beckmann et al., 2013).

2.2.3 Self-regulation

Another aspect of individual difference that contributes to performance in learning is self-regulation. Self-regulation as a research topic has historically received less substantial and in-depth research attention in comparison to topics such as cognitive abilities and personality. Research interest in self-regulation has, more recently, increased. It is now a topic of active research and discussion in many areas beyond education, for example, in social, organisational and cultural contexts. Self-regulation (or, as in some theories termed, self-control (Bandura, 1997)) is often associated with specific individual characteristics such as persistence against obstacles, delayed gratification, wise time-management, and staying on track towards desired goals. Usually, this set of characteristics is considered a skill, with particular interest paid to improving self-regulation. Self-regulation affects many aspects of our daily life, ranging from habit formation and romantic relationships to socialisation and involvement in religious practices (Vohs and Baumeister, 2016).

Self-regulation relies on a combination of individual differences, such as differences in cognitive abilities and personality traits (Wood and Beckmann, 2006). Individual differences are relatively stable constructs, but in some circumstances can be changed with the help of influential factors. These changes vary across the lifespan, most notably in early and later life (Geldhof, Little and Colombo, 2010). However, some rapid changes are also possible in between, for example, in the event of brain injury, or as the result of experiencing mental health problems. Several factors affect the development of self-regulation in early years, such as sustained attention, maternal sensitivity, and even infant temperament (Frick et al., 2018). The gradient of this self-regulatory development in childhood predicts future health, wealth, and public safety (Moffitt et al., 2011). Due to the relationship between cognitive abilities and self-regulation, self-regulatory skills might follow degenerative processes in fluid intelligence (Gf) linked to ageing:

> Cognitive processes that underpin learning are subject to age related changes. On the one hand ageing is characterised by decline, decline in working memory capacity, decline in speed of information processing, and decline in inhibitory control processes or attentional control. On the other hand ageing can be characterised by an accumulation of experience condensed in knowledge systems (e.g., schemata). The quantity and quality of such knowledge systems very much depend on the individual opportunities for and the individual level of dedicated engagement in learning activities over the life span. (Beckmann and Birney, 2012, p. 561)

A decline in cognitive skills and fluid intelligence (Gf) may lead to unwanted outcomes, such as greater exposure to daily stressors. For populations with, specifically, fully developed and unimpaired brain function (i.e. free from the early signs of the decline in brain function and age-related brain conditions such as

Alzheimer disease), various risk factors may lead to adverse outcomes in learning and later life outcomes. Attention to these aspects is outlined in Knowles' Adult Learning Theory framework (Knowles, 1978), and Kitchener and King's seven-stage model of reflective judgement (Kitchener and King, 1990). It is important, then, to account for a wide range of individuals and their changes in self-regulatory levels.

The theoretical foundation of self-regulation has benefited from research advances in the fields of neuroimaging and neuroscience, which have provided novel opportunities for adjustments of theory and practice. For instance, research in neuroscience has contributed to the identification of the possible brain regions that are responsible for controlling the desire to perform an action, and the sense of responsibility for that action (Darby, Joutsa, Burke and Fox, 2018). Utilising neuroimaging, meanwhile, has provided clues to the brain networks responsible for the human ability to control reflexive or otherwise dominant responses and to select less dominant ones (Petersen and Posner, 2012). Although neuroscience research has shown that the brain structures responsible for some of cognitive abilities are located in the prefrontal cortex region, and the same parts of the brain are also responsible for self-regulating behaviour, it is impossible to fully ascertain an equivalence between these two concepts (Saggino, Perfetti, Spitoni and Galti, 2006, p. 16). However, it is nonetheless worth mentioning the fascinating discovery that the prefrontal cortex is actively involved in the inhibition of dominant responses. Involvement in some contact sports (especially during adolescence and youth) can have a critical impact on the prefrontal lobe. For example, in sports such as football, rugby, ice hockey, and boxing, head injuries occur on a regular basis. Thus, the choice of pleasure activity or involvement in amateur sports may have a long-term impact on self-regulation and cognitive abilities.

As mentioned previously, the individual characteristics that influence self-regulation and self-regulatory behaviour are developed across the lifespan and are subject to change. More specifically, individual characteristics such as self-esteem (i.e. an individual's perception of one's own worth) (Orth, 2017), subjective well-being (Luhmann, 2017), personality (Reitz and Staudinger, 2017), perceived control (Infurna and Infurna, 2017), goals pursued and motivation

(Hennecke and Freund, 2017), attachment patterns (Fraley and Hudson, 2017), identity (Klimstra and van Doeselaar, 2017, McLean, 2017), cognitive abilities (Schmiedek, 2017) can be developed and are able to change to some extent over an individual's lifespan. In sum, it seems possible that the most influential aspects of individual differences to affect self-regulation cognitive abilities, and personality traits. Cognitive abilities and self-regulation are taken to be distinct constructs. Joel Nigg (2017) makes a distinction between self-regulation and cognitive abilities by emphasising the role of cognitive abilities and cognitive control as discrete aspects of self-regulation, which can, then, be used for other activities which are not related to self-regulation. It is evident that working memory, as part of the executive control responsible for inhibitory control, and cognitive control can be developed, at least in adolescence (Geier, Garver, Terwilliger and Luna, 2009; Luna, Paulsen, Padmanabhan and Geier, 2013).

Context-specific factors, such as physical surroundings, temporal perspective and location condition variations, are all relevant to and influence self-regulation. In the domain of online learning and self-regulation, context can be defined as a set of characteristics that surround the phenomenon in question (learners' self-regulation). Context-specific factors contribute to learners' cognition, attitudes, and behaviour. For example, being a learner from a certain country, as mentioned earlier, is likely to have an impact on online-learning outcomes.

2.3 Self-regulation in learning

Self-regulation takes on various forms, allowing for the control of emotions, actions, daily routines, and some mental processes (Ludvigsen, Cress, Law, Stahl and Rosé, 2018). However, the particular interest of this work is found within the role of self-regulation in learning. In response to the need to specify processes involved in self-regulation in learning, during the past several decades, the term Self-Regulated Learning (SRL) was developed by educational psychologists. There are several prominent theories of SRL, which are concerned with learners' achievement, behaviour, and utilisation of strategies to pursue desired learning goals. Influential and established theories include those proposed by Zimmerman (Zimmerman, 2000), Boekaerts (Boekaerts, 1999, 2017), Butler and Winne (Butler and Winne, 1995), Winne and Hadwin (Winne and Hadwin, 1998), and Pintrich (Pintrich and De Groot, 1990; Pintrich, Wolters and Baxter, 2000). These theories have consolidated theoretical and empirical backgrounds and have been broadly acknowledged as established theories of SRL by researchers and educators (Panadero, 2017). This does not, however, mean that more recently developed theories are of lesser importance or quality. Rather, they have tended to differ in terms of influence. Thus, it is reasonable to initially pay attention to the formative theories of the field, which have been tested and supported over time and have been shown to have made a significant contribution to research and practical implementations in online learning. In this section, a detailed exploration of selected SRL theories is provided, along with a description of their key components, phases, processes, and the way how self-regulation was conceptualised in these theories.

2.3.1 Zimmerman's model of self-regulated learning

Zimmerman's model of self-regulated learning made one of the first attempts to describe the self-regulatory processes involved in learning (Zimmerman, 1990). His work was, in part, influenced by Albert Bandura's research (they have co-authored a number of papers, e.g. Zimmerman, Bandura and Martinez-Pons, 1992). For example, one of Zimmerman's early works on SRL modelling can be connected to Bandura's triadic model of social-cognition, as was noted by Panadero (2017, p. 3) in his review of Zimmermans' models of SRL. In his definition of self-regulated learning, Zimmerman emphasises the role of the processes and sub-processes involved in self-regulation, rather than solely focusing on a single factor:

> Self-regulation refers to self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals. This definition, in terms of actions and covert processes whose presence and quality depends on one's beliefs and motives, differs from definitions emphasizing a singular trait, ability, or stage of competence. A process definition can explain why a person may self-regulate one type of performance but not another. (Zimmerman, 2000, p. 14)

Zimmerman's model includes three self-regulatory phases: forethought, performance and self-reflection. The first phase (forethought) includes task analysis and self-motivation beliefs and their corresponding sub-processes: goal setting and strategic planning relate to the former; self-efficacy, outcome expectations, intrinsic interest (value), and goal orientation, which are relevant to the latter. The second phase (performance) includes self-control and self-observation. Self-control consists of the next set of sub-processes: task strategies, self-instruction, imagery, time-management, environmental structuring, help-seeking, interest incentives, and self-consequences. Self-observation includes metacognitive monitoring and self-recording sub-processes. The third phase (self-reflection) of Zimmerman's cyclical model of SRL consists of self-judgement divided into self-evaluation and casual attribution, and self-reaction, composed of self-satisfaction (affect) and adaptive (defensive) sub-processes (Zimmerman, 2002, p. 67).

According to Zimmerman, learners acquire their competency in SRL through four developmental phases: observation, emulation (the practising of observed behaviour), self-control and self-regulation. Involvement with these four phases means that first, learners observe behaviour as it is demonstrated by a proficient model, and, second, they are then able to imitate the performance by applying the general pattern or style of the model with social assistance. Third, they seek positive feedback and encouragement and, in their final step, learners find motivated in their personal efficacy beliefs. In addition, motivation occurs during each for the four phases (Zimmerman, 2000, p. 25-26).

2.3.2 Winne's model of self-regulated learning

An introduction to Philip Winne's model requires the consideration of Winne's broader collaborations, including his work with Butler (1995), collaboration with Hadwin (Winne and Hadwin, 1998, 2008), and Winne's single-authored works (Winne, 1996, 2017a). The significance of the earlier models should not be underestimated as these models have been widely used[1], and provide valuable

[1]At the time of writing, the study of Butler and Winne (1995) has 1381 citations in Scopus citation database.

conceptualisations of the role of feedback, engagement, and motivation in self-regulated learning.

Butler and Winne's model of self-regulated learning is based on theories of information-processing, and this model, as it was initially proposed in 1995, includes four phases: i) external (utilising available resources that are external to the learner) and internal (relying on memory as a resource) information searches relevant to a task at hand; ii) goal setting and the creation of a plan to achieve the set goals; iii) working on the task with the extracted information toward the goal(s); iv) evaluation of progress and goal adjustment (if required) (Butler and Winne, 1995). In his more recent work, Winne has identified several basic cognitive processes involved in SRL. These processes correspond to higher level operations performed by learners: searching (providing attention to information), monitoring (identifying suitable information), assembling (combining separate information by identifying relationships), rehearsing (preserving information), and translating (transforming the representation of information provided) (Winne, 2017a, p. 37). All of these processes require an allocation of learners' cognitive resources.

2.3.3 Boekaerts' model of self-regulated learning

Boekaerts' model of self-regulated learning (Boekaerts, 1999) is a result of years of theoretical and practical research devoted to the topic of learning and learners' self-regulation. The model includes a three-layered process structure, with the learning process at its core (i.e. the inner layer), regulation of the learning process as the middle layer, and regulation of oneself as the outer layer. The inner layer includes several aspects of the learning process, such as how learners process information, and how they might select and organise cognitive strategies in order to achieve learning success. The middle layer includes processes related to the choice of metacognitive strategies to facilitate selection, monitoring and control of the learning process. The outer layer is focused on goals and resources, motivational regulation, and protecting a learner from competitive distractions.

As Boekaerts' research has evolved over time, she has made adjustments to her initial model to highlight the role of emotions on self-regulation (Boekaerts, 2011). More recently, she has proposed a connection between cognitive load and SRL strategies (Boekaerts, 2017). In addition, she has returned to her three-layered process model, proposed two decades earlier, emphasising the need to consider affect, goals and motivational regulation strategies, in order to form a link between research on cognitive load and self-regulated learning (Boekaerts, 2017, p. 96).

2.3.4 Pintrich's model of self-regulated learning

Pintrich breaks down self-regulated learning into four parts in his model (Pintrich et al., 2000): cognitive, motivational, affective, behavioural and contextual aspects, forming four SRL phases. These four SRL phases include: i) forethought, planning, and activation; ii) monitoring; iii) control; iv) reaction and reflection. In his model, Pintrich effectively synthesised previous works on SRL, including research by Winne and Zimmerman, to present his definition of self-regulated learning. According to Pintrich's model, the main scaffold of self-regulated learning is metacognition and metacognitive knowledge:

> Taken together, planning, strategy selection, resource allocation, and volitional control comprise four important aspects of self-regulation and control. In combination with metacognitive judgements and monitoring, they make up the "on-line" process-oriented aspects of metacognition and self-regulated learning. The "static" component of metacognition, metacognitive knowledge, once activated in a situation, is an important resource that is drawn upon by learners as they monitor and control their own learning. (Pintrich et al., 2000, p. 53)

In addition, alongside the described model and other contributions to research on SRL, Pintrich and his colleagues developed a self-regulating motivation strategies scale, which is a widely used instrument to assess learners' self-regulatory characteristics (Moseley et al., 2005, p. 235).

2.4 Self-regulation in the context of online learning

The diversity of models of self-regulated learning and their application across many tasks, contexts, and learners' groups makes it challenging for researchers and practitioners to select the most suitable model for application it in practice to guide the design of curriculum, educational policy or as an instrument to support learning. SRL models have evolved over time; many early models have been significantly modified by their creators over time. Additional empirical evidence and further theorisation has brought, in tandem, modified conceptualisations of established models. Researchers and scholars have replaced and added 'features' to existing models, renaming and reconceiving of, for instance, the dated concept of 'learning styles', transformed into the concept of 'learning patterns' (Vermunt and Donche, 2017, p. 276). The evolution of SRL models is not always justifiable, and it is perhaps confusing to unfold another modified version of an established model when there is no accompanied acknowledgement of its significance over a preexisting model or accompanying rationale for the update. However, theoretical perspectives on self-regulation in educational settings have a number of features in common. First, self-regulation includes behaviour, cognitive, metacognitive, and motivational participation in learning and performance. Second, goal setting helps learners to focus on tasks and related activities. Third, self-regulation is a dynamic process. Fourth, motivation is critical for learning and can affect goals. Fifth, emotions are important for self-regulation and pursuing goals (Schunk and Greene, 2018, pp. 1-2).

Conceptualising self-regulation in online learning is a difficult task, as several factors influence its complexity. First, online learning is rapidly changing, which presents a challenge when attempting to focus on a specific feature, for example, the growing popularity of mobile learning apps and the forthcoming virtual and augmented reality revolution. Second, proposed models of self-regulation are modified by their creators over time, creating mutually incompatible empirical evidence as a result of differences between groups of learners, contexts, and distinct learning tasks. Furthermore, theorists have a tendency to avoid acknowledging the weaknesses of earlier versions of their models, making it more challenging to build upon them (in theory and in practice) due to the unmanageable variety of versions. Finally, self-regulation is in itself a complex concept which includes several dimensions based on physiological nuances. However, neuroscientific and psychological research has made some progress in identifying physiological and mental constructions which determine self-regulation. The conceptualisation of self-regulation in online learning provided in this chapter builds upon the characteristics of online learning described in the first chapter, including major theoretical frameworks for the thinking processes involved in learning, research on individual differences involved in self-regulation, such as cognitive abilities, personality traits, general self-regulatory skills, and context-specific factors that contribute to learning, and, finally, the established models of self-regulated leaning, which are based on information processing and social-cognitive perspectives.

The theoretical foundation presented in Section 2.1 and summarised in Section 2.1.8 suggested the hope that learners' self-regulation can be developed or compensated for in certain situations (e.g. when development is not possible). Learners' individual differences, as covered in Section 2.2, play a crucial role in the developmental and compensatory processes. Individual differences encompass a range of factors, such as learners' cognitive abilities, personality traits, and levels of self-regulation. Self-regulation consists of different stages, and feedback to learners is involved at each stage (according to the SRL models proposed by Zimmerman, 2000, and Butler and Winne, 1995; Winne, 1996). Based on these models, it seems reasonable to assume that to ensure that feedback to learners is effective, it is necessary to (1) identify the right moment (i.e. the 'starting point' or initial state for providing scaffolding) when feedback should be delivered to learners; (2) take into account learners' individual differences in the process of generating and providing feedback, and (3) deliver feedback based on performed behaviour.

Conceptually, learners' self-regulation is not a unitary construct. Rather, it is characterised by 'many types of self-regulated action that are more or less appropriate for different tasks, in different domains, in different socio-cultural contexts, and for different students' (Kaplan, 2008, p. 483). In terms of choosing a specific SRL model as the most appropriate direction for further investigation and intervention design, Zimmerman's (2000) notion of SRL multidimensionality seems the most relevant to the present study. In contrast to focusing on individual self-regulatory processes, such as goal setting and strategy use, Zimmerman choose another approach. His effort to unite distinct elements into a multifaceted construct led to the multidimensional view on learners' self-regulation

(Zimmerman, 2008). The multidimensional approach to learners' SRL explains why some learners may self-regulate on a certain task while others experience difficulty. Furthermore, Zimmerman's model of SRL is rooted in social-cognitive aspects of human development and change, proposed by Vygotsky (described in Section 2.1.1) and Bandura (described in Section 2.1.7).

This social-cognitive theoretical stream has been highly influential in educational psychology (Ardila, 2016; Vasileva and Balyasnikova, 2019), professional development (Eun, 2019), adult learning and higher education (Rosser-Mims, Dawson and Saltiel, 2017), and research on learners' self-regulation (Usher and Schunk, 2018). Therefore, Zimmerman's model of self-regulated learning seems the most promising direction for further investigation. There are three prongs to the application of Zimmerman's social-cognitive approach to self-regulated learning. First, this approach distinguishes the effects of learners' individual differences from differences in their behaviour. Second, it links learners' self-regulatory processes with performed behaviour. Third, it highlights two important processes that contribute to self-regulated learning, particularly, self-efficacy perceptions and the utilisation of SRL strategies (Zimmerman, 1989, p. 337). Following the social-cognitive approach to learning, it is then assumed that learners' self-regulation is both observable and trainable through an intervention that leads to a specific experience (Zimmerman, 1989). This assumption is in line with the multi-layered view on learners' abilities, indicated in Carroll's three stratum theory of intelligence (Carroll, 1993) and Fierstein's notion of cognitive modifiability (Feuerstein and Jensen, 1980). The limitations of this approach to SRL are primarily derived from the works underpinning Zimmerman's model. For example, in the case of Bandura's social learning theory (Bandura, 1971), learners' individual differences, environment modifications and learners' behaviour are emphasised. However, little attention is paid to a learning task. In the case of Vygotsky's works, as mentioned earlier (Section 2.1.1), identifying the correct level of prior learners' self-regulation to indicate a starting point for delivering an intervention can be challenging.

In conclusion, self-regulation in online learning is a skill which can be developed, compensated for, and observed. 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. More specifically, planning includes a survey of available resources, goal setting, and the development of strategic and tactical intentions. Monitoring entails the observation of performed behaviour and its consequences. Self-control consists of selecting behaviour that is conducive to achieving set goals and avoid behaviour that distracts from achieving them. Self-evaluation includes a survey of performed actions and contrasting outcomes with set goals. This set of internal mental components is a relatively stable construct in which dimensions are subject to change depend on the interplay of three dimensions: learners' individual differences, learning tasks, and situational characteristics, according to the PTS framework.

Each dimension of self-regulation in online learning can impact self-regulatory behaviour independently or as the result of interaction between dimensions. Combinations of relatively stable personal characteristics such as cognitive abilities and personality traits facilitate the development and compensation of self-regulation in online learning. Task-situational characteristics, such as distractions and provided instructions contribute to self-regulatory performance.

3 | Operationalisation of Self-Regulation

The detailed descriptions of theoretical frameworks, self-regulatory models and individual differences presented in the previous chapter have provided a summary of the processes required for self-regulation in online learning environments. Chapter two demonstrated the ways in which affective, cognitive, metacognitive, and motivational components are influenced by learners' individual differences, e.g. cognitive abilities, personality traits, and context-specific factors, such as the presence of distractions. Accordingly, self-regulation is considered a skill that can be developed and a lack of it can be compensated for. This chapter continues the efforts of this thesis to gain a better understanding of how online learners can effectively utilise the opportunities provided by online learning, and especially by online learning at scale. Here, particular attention will be given to the operationalisation of self-regulation.

3.1 Self-regulation as engagement with learning

The primary function of self-regulation in adult and online learning is to facilitate learning and to stimulate the learning process. It is acknowledged that adult learning occurs in a broad range of settings or the field (Beckmann and Birney, 2012, p. 561). Online learning, similarly, might happen in a diversity of web resources and learning is affected by the learning task (e.g. content), the learning situation (e.g. online learning environment), and the learner (e.g. their prior knowledge and experience). To enable learning in online settings, learners need to engage in the learning process. Engagement with learning can be broken down into the following: academic engagement, behavioural engagement (behavioural manifestations), and engagement at the level of mental components involved in learning.

3.1.1 Academic engagement

Academic engagement involves the application of learning strategies. Learning strategies, such as those associated with social learning and self-regulated learning, are essential mediators of academic achievement and learning in traditional learning settings as well as MOOCs (Magen-Nagar and Cohen, 2017). The application of self-regulated learning strategies facilitates learning engagement. Learners apply different self-regulatory strategies, depending on their individual differences, the learning task at hand and situational characteristics. Zimmerman and Martinez-Pons (1986) proposed a range of categories encapsulating self-regulatory strategies. This range of strategies includes: self-evaluation; organisation and transformation of notes; goal setting and planning; seeking information from external resources; keeping records, monitoring of notes and achieved results; environment re-structuring; self-consequence; memorisation and rehearsing learning materials; seeking assistance from peers; seeking assistance from senior academics; seeking assistance from teaching assistants and other sources of support; reviewing previous problem sets; reviewing notes; reviewing textbooks and other assigned materials, and other categories of strategies (Zimmerman and Martinez-Pons, 1986, p. 618).

Based on self-regulated learning (SRL) theories and the categories mentioned above, Lopez, Nandagopal, Shavelson, Szu and Penn (2013) have conducted an analysis of 89 participants' study diaries, concept maps, problem sets, and final course grades in order to ascertain the benefits of the various learning strategies that dominate online learning. Authors have shown that students predominantly engage in four reviewing-type strategies: 'organising and transforming', 'reviewing previous problems', 'reviewing notes' and 'reviewing text' (Lopez et al., 2013, p. 669). Although Lopez et al. do not specify how the use of these strategies might correlate with course completion rates, they do, nonetheless, demonstrate that using an 'Organising and transforming' strategy correlates with a learner's average concept map score, and average problem set score. However, there were no reported correlations between the strategies mentioned and final course grades (Lopez et al., 2013, p. 670). Therefore, some of the SRL strategies that emerged from Zimmerman's model of SRL are involved in the learning process and associated with intermediate learning outcomes, expressed in learners' average concept map and problem set scores.

Another classification system for self-regulated learning strategies has been provided by Kizilcec, Pérez-Sanagustín and Maldonado (2017). This theoretical classification, which focuses on online learners, is based on a review of theories of SRL and proposed models. Kizilcec et al. provide six categories for SRL strategies which affect course completion and learning outcomes: goal setting, strategic planning, self-evaluation, task strategy (includes time management), elaboration, and help-seeking (Kizilcec et al., 2017, p. 21). The empirical part of their study reinforces the assumptions proposed in Zimmerman's conceptual model of SRL (Zimmerman, 2000). Kizilcec et al.'s study concludes that learners who apply goal setting and strategic planning strategies are more likely to achieve their personal course goals. However, help-seeking strategies were also negatively associated with goal attainment, that is those who seek more help tend to struggle more with completing their course (Kizilcec et al., 2017, p. 27).

The reported learners' self-regulatory strategies are not an absolute predictor of performance; other strategies can be extracted from less dominant SRL models and online learning environments, such as those that require learners to utilise creativity to stay persistent with their learning. In their early work, Zimmerman and Martinez-Pons (1986) included a strategy category, labelled 'Other', to indicate 'Statements indicating learning behavior that are initiated by other persons, such as teachers or parents, and all unclear verbal responses, e.g., "I just do what the teacher says."' (Zimmerman and Martinez-Pons, 1986, p. 618). Nevertheless, academic engagement in learning involves the application of self-regulated learning strategies as a mediator of affective, cognitive, metacognitive and motivational components involved in SRL, and this engagement is manifested in behavioural terms. In online learning, and particularly in MOOCs, learners' academic engagement is predominantly measured by the time spent on course activities, the number of days dedicated to learning (i.e. engaged with a course) and the completion of assessments, exams and the full course' curriculum, alongside pretest and posttest results, as summarised in the systematic review conducted by Joksimović et al. (2018, p. 67).

3.1.2 Behavioural engagement

Learners' utilisation and successful application of self-regulatory strategies in online learning environments can be traced in the form of learners' digital footprints. These markers could include a course of performed actions, steps taken to desired goals and participation in certain activities. These footprints are usually logged by Learning Management System (LMS)s, referred to in the research literature as digital traces. A plethora of research has analysed learners' activity using log files from learning management systems, ranging from note-taking and participation in a collaborative activity to clickstream data, and interruptions during video watching activities. These studies usually report certain indicators and their association with learners' individual differences, such as levels of self-regulation, learning experience, and motivation. Some of the research conducted to date has been solely data-driven, whereby learners' actions are clustered into groups that represent their levels of self-regulation. For example, the examination of online learners' behavioural sequences in the form of clickstream data obtained from 5,764 learners (Min and Jingyan, 2017) and navigational patterns from 332 participants (Jeske, Backhaus and Stamov Roßnagel, 2014) demonstrates that behaviour traces are related to course grades (Min and Jingyan, 2017), learning experience and test performance (Jeske et al., 2014).

In another cohort of studies, in addition to traces drawn from learning management systems, self-report SRL questionnaires have also been administered. For example, an analysis of 4,831 learners across six MOOCs conducted by Kizilcec et al. (2017) demonstrated that learners with high levels of self-report SRL (except for help-seeking) engaged in behaviour associated with revising course content more frequently than those with low self-report SRL scores. In their work, authors examined 22 possible variables of SRL strategies, and report that learners with high scores in help-seeking were less likely to pass their assessments (Kizilcec et al., 2017, p. 27).

Self-regulation as a mark of behavioural engagement with learning can be derived using qualitative data and multiple data sources. For example, Min and Foon (2019) measured patterns associated with levels of self-regulation using a qualitative approach. The authors conducted email interviews with 83 learners, predominantly from China ($N = 58$) and Hong Kong ($N = 18$), with questions on behavioural, emotional, and cognitive engagement in online learning situations. The authors compared received responses with selected indicators of engagement associated with the three-stage model of SRL (described in Section 2.3.1 on page 42), and its nine sub-processes, as proposed by Zimmerman (2000). Min and Foon concluded that the first stage of SRL (forethought) was responsible for the activation of behavioural regulation (applying task and time management strategies). Behavioural regulation was also observable during the performance phase, while affective regulation appeared in the forethought and self-reflection stages, but was not utilised by learners during the performance stage. Cognitive regulation was involved during each SRL stage (Min and Foon, 2019, pp. 101-102). As another illustration of approaches to using multiple data sources, Kaplan, Lichtinger and Margulis (2011) have demonstrated that multiple data sources relating to behavioural engagement (including micro-process observations, traces in the written product, stimulated-recall, and general interviews) can be effectively cross-validated, and applied to assess the dynamic and situated processes involved in self-regulated learning.

The approaches to measuring self-regulation as behaviour engagement mentioned above have been shown to be suitable for a variety of tasks and learning environments. Overall, behavioural engagement is based on the idea of participation, which includes learners' interactions with learning resources, such as learning content, supplementary materials, and discussion forums, and analysing these engagements in order to measure behaviour engagement (Joksimović et al., 2018, p. 67). However, one common disadvantage of the approaches applied in the previously mentioned studies is that their results rely on self-reporting and/or traces drawn from learning management systems that do not take into account antecedent (prior accessing LMS) and consequent (followed by accessing LMS) behaviour. Therefore, approaches outlined tended to exclude learners who do not login in their their learning management systems. Furthermore, operationalisation of SRL in the field (i.e. natural settings) might benefit from constructing a complete picture of learners' behavioural engagement in two ways. The first: complement self-report data with behaviour traces and vice versa. The second:

taking into account learners' behaviour outside LMS, as learners' behaviour that appear outside of the scope of LMS might provide additional insights into learners' self-regulation and behavioural engagement.

3.1.3 Components involved in engagement with online learning

Self-regulation in online learning, as conceptualised in the previous chapter, includes affective, cognitive, metacognitive, and motivational components. As outlined previously, the common practice to assess SRL is by focusing on learners' metacognition, including self-regulatory strategies employed by learners and their behavioural manifestations. In terms of other components involved in learners' SRL, a systematic review of research on MOOCs conducted by Joksimović et al. (2018) has shown that cognitive and affective engagement have historically been assessed using linguistic indicators (e.g. messages posted by learners in their course forum discussion board) (Joksimović et al., 2018, p. 68). The choice to utilise linguistic indicators is likely explained by data availability, and the fact that these studies are predominantly based on self-report data or behaviour observations from LMS.

It can be assumed that utilisation of additional data sources beyond LMS would provide other crucial indicators of the mental components involved in engagement with learning. In terms of cognitive load (Sweller, 2011), for example, shifts in learners' attention between learning resources (Mayer, 2018), and external tools, such as machine translation services, search engines, and other information resources that assist with obtaining and processing information, may indicate an increase in cognitive demand. It seems necessary, therefore, to go beyond the data-tracking limitations of LMS in order to obtain a more comprehensive picture of the components involved in engagement with learning, and their behavioural manifestations. While this approach, including data beyond LMS, adds additional complexity to research, data obtained within LMS provides rich sources of insight. For example, Lust, Elen and Clarebout (2013) demonstrated that tools to support learning provided within an LMS that induce higher-order thinking are often ignored by learners (p. 393).

To conclude this section, self-regulation in online learning — and particularly learning at scale (Section 1.3.3) — can be operationalised by applying a range of different, complimentary approaches: by tracking SRL strategy use; tracking the occurrence of self-regulatory cyclical phases (planning, monitoring and self-control, self-evaluation); and by tracking the dynamic of self-regulatory components (affective, cognitive, metacognitive, and motivational). A different level of granularity can be applied to these approaches. It seems possible that assessing SRL based on self-report and behavioural data collected beyond learning management systems can be helpful to exploring learners' self-regulation, and what might trigger learners to switch their attention from LMS to other resources, and vice versa. Integrating the latter component would provide a range of insights into the antecedents and consequences of learners' self-regulatory practices and its complex dynamics.

3.2 Failure of self-regulatory behaviour

3.2.1 Components involved in the failure of self-regulatory behaviour

Some of the individual differences that affect a learner's self-regulation are likely to change over one's lifespan. Alongside short-term situational changes, learners' affective, cognitive, metacognitive, and motivational components can undergo long-term changes. For example, it has been reported that metacognitive efficiency increases in adolescence, stabilises in early adulthood, and declines with age (Palmer, David and Fleming, 2014). External factors reinforce the trend for change over time.

Self-regulation requires four mechanisms (Kelley, Wagner and Heatherton, 2015). The first includes an awareness of one's behaviour in order to be able to compare it with established norms. Second, an individual needs to understand the consequences of their behaviour. Third, an individual needs to be aware that possible threats might manifest as the result of their own behaviour, alongside the consequences of not performed behaviour. Finally, an individual needs to find a compromise between one's own and external expectations (i.e. learned norms), seeking to rectify any discrepancy between them (Kelley et al., 2015, p. 393). While these four mechanisms might work well in traditional classroom settings, in online settings (especially in the context of instructionalists' xMOOCs where instructions dominate over social interactions), these four mechanisms, required for self-regulation, might not be present. As a result, learners may experience failures in self-regulatory behaviour:

> In healthy adults, self-regulation failures often occur in the presence of a highly desirable reward cue, particularly when the cue follows a precipitating event, such as emotional distress or exhaustion of self-regulatory resources. Successful self-regulation therefore requires a balance between the strength of reward cues and the capacity to keep them in check [(Heatherton and Wagner, 2011)]. As such, self-regulation failure can occur in response to an overwhelming impulse or when the capacity to self-regulate is impaired or absent. Three common threats to this balance have been identified: exposure to tempting cues (e.g., food, drugs), emotional and social distress, and depletion of self-regulatory resources. (Kelley et al., 2015, p. 390)

As mentioned by Kelley et al. (2015), emotional and social distress, deficits in self-regulatory resources, and exposure to tempting external cues (e.g. social media websites, which have addictive qualities (Osatuyi and Turel, 2018)) may lead to failures of self-regulatory behaviour. Online learners might have an increased risk of experiencing problems with self-regulation due to the specific qualities of online learning environments. Therefore, it is vital to understand the mechanisms involved in the failure of self-regulatory behaviour in order to identify, prevent and intervene in its negative pathways.

A deficit in one or several components involved in SRL may lead to the failure of self-regulatory behaviour (i.e. procrastinatory behaviour). A survey with 7,400 participants conducted by Steel, Svartdal, Thundiyil and Brothen (2018) to determine the epidemiology of procrastination demonstrated that, in the majority of cases, procrastination could be explained with critical aspects of self-regulation, including attention control, energy regulation (which has been understood by authors to demand significant mental components), and automaticity (defined by authors as a habitualised course of actions that require minimal or no conscious attention). These factors accounted for the majority (74%) of the variance in procrastination (Steel et al., 2018, p. 13). Therefore, procrastinatory behaviour can be divided into two categories: controlled and uncontrolled procrastination. Learners might be engaged in controlled procrastination purposefully, for example, in case of cognitive overload, they might deliberately free their cognitive resources required to accomplish a task by switching their attention to an activity that required less demand on their cognitive resources. Uncontrolled procrastination may occur involuntarily, due to working memory (cognitive) overload, emotional distress, and motivational problems when attempting to engage in certain activities. It can be hypothesised that procrastinatory behaviours can be expressed in certain measures and can be tracked as a set of patterns.

3.2.2 Controlled and uncontrolled procrastination

Under the umbrella of the notion of 'controlled procrastination', it is assumed that, instead of a learning session, learners might be involved in beneficial, self-aware procrastinatory activities. This controlled procrastination might occur after a high-intensity or lengthy studying session, when a learner seeks relaxation or an activity with low-level cognitive demand — similar to cognitive offloading (reliance on external resources to reduce cognitive demand, as defined in Hu, Luo and Fleming, 2019). Some learners can use controlled procrastination as a motivator, e.g. after studying for one hour, learners can allow themselves ten minutes of 'Facebook time'. These activities are considered productive and useful to learning.

'Uncontrolled procrastination' assumes that learners are unintentionally engaged with counterproductive activities, due to the failure of self-regulatory behaviour. Such failure could be attributed to several causes, for example, experiencing excessive stress levels. It is evident that many learners experience mental health problems, with anxiety and depression prevalent among graduate students (Evans, Bira, Gastelum, Weiss and Vanderford, 2018) as well as those in primary, secondary and further education (Tremblay et al., 2011). A significant number of school-age children have been found to have low self-esteem, alongside problems associated with excessive sedentary behaviour, screen-time, and extensive use of social media (Tremblay et al., 2011). Time spent on social media and overall screen-based media interactions significantly correlate with a decline in well-being among young people, which appears to have an effect on their long-term performance at school and life outcomes. This is particularly relevant for female pupils (Booker, Kelly and Sacker, 2018).

A systematic review of published studies (Suchert, Hanewinkel and Isensee, 2015) and a meta-analysis of observational studies (Liu, Wu and Yao, 2016) have shown that screen time and screen-based sedentary behaviours are connected to anxiety and depressive symptoms, inattention, problems with hyperactivity, low self-esteem, a low sense of well-being and overall quality of life. Although little is known about the proportion of online learners who experience symptoms related to anxiety and depression, it can be estimated that the nature of online learning environments — with the absence of university health services, reduced instructor and peer support, prevalence of exposure to screen time and sedentary behaviour — anxiety and depression are likely to be at least as typical as for school-age children and students enrolled in graduate-level courses. Despite the absence of straightforward evidence to support this claim, this assumption can be traced in emerging research, for example, a protocol of a randomised control trial aiming to evaluate the effectiveness of internet and app-based stress interventions for distance-learning students with depressive symptoms has recently been published (Harrer et al., 2019).

Based on the assumption that a significant proportion of online learners may experience symptoms related to anxiety and depression, it is crucial to understand how these psychological issues may affect the learning process, and what effects they might have on learners' engagement. Based on research in psychology and neuroscience, a dynamic framework for understanding mind-wandering has been proposed (Christoff, Irving, Fox, Spreng and Andrews-Hanna, 2016). This framework links mind-wandering to depression and anxiety, characterised by one's involvement in repetitive, automatic actions:

> Overall, depression seems to be characterized by excessive stability in thought. [...] One hallmark of depression is rumination, which is defined as "repetitively and passively focusing on symptoms of distress"

> and remaining "fixated" on one's problems and one's feelings about them. [...] Rumination is largely involuntary: individuals with depression may want to stop themselves from ruminating but are often unable to do so, suggesting that the constraints on thought in rumination are primarily automatic. (Christoff et al., 2016, p. 725)

> Like depression, anxiety disorders are characterized by repetitive negative thoughts [...] Within our framework, both anxiety and depression are marked by excessive automatic constraints on thought. These constraints may differ, however, in terms of the level of cognitive processing at which they begin. (Christoff et al., 2016, p. 726)

Based on this description of depression and anxiety, it might be worth attempting to track repetitive patterns as part of the process of identifying learners' involvement in uncontrolled procrastination, that negatively affect learners' engagement with their online course. This is due to some learners may experience problems in dealing with the affective, cognitive, metacognitive and motivational demands of online learning and may develop symptoms related to depression and anxiety. In this case, uncontrolled procrastination is considered to be counterproductive behaviour.

3.3 Measurements of self-regulation and its failure

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 and Foon, 2019), think-aloud protocols and unstructured interviews (Greene and Azevedo, 2010), clickstream data (2017), microanalytic methods (Cleary and Callan, 2018), and data mining methods (Biswas, Baker and Paquette, 2018) applied to traces of behaviour (Azevedo, Taub and Mudrick, 2018), including navigation patterns (Jeske et al., 2014). This range of approaches can be characterised by three pairs of assessment categories. The first pair classifies SRL assessment approaches using self-report and behavioural measures. The second pair classifies reported SRL assessment approaches into macro and micro levels (for self-report data) or levels of granularity (for behavioural traces). The third pair classifies SRL assessment approaches according to two strategies:

measuring self-regulatory cyclical phases and measuring components involved in SRL. Thus, an assessment of SRL can be described by its type of measurement, its degree of detail (i.e. its level of detail) and its strategy.

The difference between the components of the first pair of classifications (i.e. between self-report and behaviour measures) is that self-report measures – internal — versus behaviour measures — external. The other terms (classification pairs) require more detailed explanation. Based on the work of Azevedo, Moos, Greene, Winters and Cromley (2008), Greene and Azevedo (2009) have provided examples of the micro and macro-level aspects of students' self-regulatory behaviour. Examples of the macro-level include planning, monitoring, SRL strategy use, task difficulty and demands, and interest. Examples of the micro-level include instances of planning (e.g. setting goals), monitoring (e.g. monitoring one's progress towards a goal), strategy use (e.g. selecting a new source of information), task difficulty and demands (e.g. help-seeking behaviour), and interest (e.g. interest statements) (Greene and Azevedo, 2009, pp. 25-27). Analysis of processes at the micro-level can be approached by using data exploration of behaviour measures (i.e. traces, see, for example, Siadaty, Gašević and Hatala, 2016), or using a self-report approach, such as an interview. To assess SRL at the micro-level using interview data, the SRL microanalysis technique was developed (Cleary, Callan and Zimmerman, 2012). The application of microanalysis to assess individuals' regulatory processes can be traced back to Bandura's microanalysis, which was used to evaluate shifts in self-efficacy beliefs and the relationship between these shifts and behaviour performance in response to anxiety-reduction interventions (Cleary and Callan, 2018, p. 340). As mentioned earlier, approaches to assess SRL revolve around two strategies. First, self-regulatory cyclical phases (planning, monitoring, self-control, self-evaluation) are measured. Second, SRL is measured as a set of characteristics of learners' affective, cognitive, metacognitive, and motivational components.

3.3.1 Self-regulation as an event

To operationalise self-regulation in online learning, components involved in self-regulation (affective, cognitive, metacognitive, and motivational) could be represented in the form of traceable events. First, to measure cognitive demands on learners during online study sessions, the frequency of interactions between the learning environment, educational resources, and other resources related to learning can be considered. For example, these events can be represented as the rate of occurrence when a learning session was interrupted by the need to reach for an external resource, such as a search engine or translation service (to find a definition of an unfamiliar concept, or to translate an unfamiliar word in cases when the language of instruction is not the learner's first language).

Second, it can be assumed that processes of metacognition (i.e. learners' awareness of their involvement in planning, monitoring, control, and evaluation processes) are expected to manifest in events relating to goal setting and adjustment, the occurrence of self-monitoring, and the absence of actions that learners considered to be undesirable (i.e. undesirable actions can be constituted as, for example, if a learner had indicated a particular web resource that they wished to avoid, which is then repeatedly accessed). In addition, processes of metacognition are expected to manifest in a learner's behaviour (e.g. frequency of times the learner visits web-pages to set goals, monitor progress, and evaluate their off-task behaviour).

Third, the affective component includes a range of emotions. The emotional aspect of self-regulation can be divided into two dominant and relatively independent dimensions: positive and negative affect, which can be measured, for example, by self-report mood scales (Watson, Clark and Tellegen, 1988). It is acknowledged that students' experience of certain emotions negatively affect learning outcomes. Baker, D'Mello, Rodrigo and Graesser (2010) have delineated a detailed set of emotions associated with the learning process: boredom, frustration, confusion, engaged concentration, delight, and surprise. Boredom and confusion are the most prominent emotions to consider in detail. On the one hand, both these emotions can be regarded as a potential antecedent of learning (positive effects) as they provide an opportunity for learners of experiencing cognitive conflict with their learning task, and attempting to resolve this conflict could result in learning outcomes, according to Piaget's cognitive disequilibrium (for a discussion on this effect in online learning setting, see, for example, Lehman, D'Mello and Graesser, 2012). On the other hand, boredom and confusion can be considered as counterproductive emotions. For example, a meta-analysis of 29 studies (Tze, Daniels and Klassen, 2016) confirmed that, in classroom settings, boredom negatively affects learning outcomes, academic motivation, study strategies and behaviours. Also, as these emotions occurred, learners tried to game their learning system, as it was shown by Baker et al. (2010). Despite the relatively low frequency of appearance for the other emotions delineated, boredom appeared to be a persistent state across learning environments. Boredom was found to occupy, on average, 4-6% of the time learners spent interacting with their learning platform (Baker et al., 2010, p. 236).

Boredom seems to be the most influential emotion on learners' self-regulation. Boredom detection, complemented by intervention, could be a prominent step to take in improving learners' affective engagement. Boredom can be considered as the opposite of engaged concentration. Engaged concentration was operationalised by Baker et al. (2010) as behaviour that includes 'immersion, focus, and concentration on the system, with the appearance of positive engagement' (Baker et al., 2010, p. 232). Boredom was defined by the authors to be behaviour that indicates disengagement from the learning process. It can be assumed that boredom are expected to manifest as the rate of occurrence (i.e. the number of incidences) and the rate of re-occurrence (i.e. persistence) of events related and unrelated to learning behaviour. More precisely, boredom can be expressed in the number of times learners engaged with their learning environment and then switched to not-relevant to learning web resources (e.g. social media, news, and online games) and the proportion of time learners contributed to these activities.

Forth, measuring motivational processes in the filed is considered to be one of the most challenging tasks (Azevedo et al., 2018). A learner's behaviour towards certain resources can, however, be considered to be a suitable indicator for motivation. For example, Dawson, Macfadyen and Lockyer (2009) has demonstrated that motivational aspects of learners' behaviour can be predicted at scale by analysing learners' participation in discussion forums. Student achievement orientation significantly correlates with participating in forum discussions: learners with a stronger learning orientation tend to participate more in the ‘learning forum’, while students with performance orientation are more likely to use the ‘administration forum’ (Dawson et al., 2009). The idea of dividing available resources into categories can be extended further, beyond the boundaries of learning environments. All of the information resources utilised by learners can be labelled with corresponding categories, such as social media platforms, resources used for entertainment, and resources used for productive work. Changes in the time and frequency of accessing such categories may indicate changes in learners’ motivational states. This is the approach which can be taken to measure the motivational component involved in SRL.

3.3.2 Failure of self-regulation as an event loop

In addition to measuring the components involved in SRL, measuring failures of self-regulatory behaviour could also include procrastinatory behavioural patterns. It seems possible to detect such patterns of controlled and uncontrolled unproductive behaviour using trace data. As in the case of self-regulation in learning, which is cyclical (e.g. a sequence of goal setting, self-monitoring and self-control, self-evaluation, goal adjustment, self-monitoring, etc.) it seems possible that failures of self-regulatory behaviour are associated with automatic repetitive actions, which similarly have a cyclical nature, and can be imagined as a sequence of repetitive events, expressed in web navigation behaviour.

Learners may engage in activities of which they are unaware, for example, extended controlled procrastination might shift to uncontrolled procrastination. As an illustrative example, a learner studying on a course web page might come across new, unfamiliar concepts. They might then desire to understand these, moving on to a Wikipedia web page, or asking questions on the question-and-answer website, such as quora.com, in order to dive into the nuances of these topics. After reading for a while, the learner might click on a somewhat related topic, but might end up with participating in an off-topic debate on quora.com. Another example of self-regulatory dysfunctional behaviour might be a situation in which a learner experiences anxiety or another form of negative and unproductive thought, which might affect their capability and motivation. For instance, imagine if the learner has a vital exam the following day, failure of which might lead to their dropping out of university, and the learner has limited confidence in their performance. In this case, the learner might struggle to prepare for the exam at all, due to the lack of confidence; they might then find themselves trapped in maladaptive thoughts. Unproductive thoughts, in turn, might drain the learner's cognitive resources, estranging them from productive behaviour. To illustrate this in measurable events: a learner could start a learning session by opening a course web-page, then switch their attention to web resources, unrelated to learning, which require low-level cognitive activities, such as checking email, Facebook's news feed or scrolling through the comments on any popular online media, news or entertainment website.

In terms of tracing such behaviour, events related to participating in a learning activity (time spent on a course, or course-related web pages) and controlled procrastination (limited time spent on entertainment websites after learning sessions) can be attributed to the productive and intended behaviour. Events related to uncontrolled procrastination (failure to self-regulate), in terms of the appearance of frequent repetitive behaviour patterns in a learner's web navigation behaviour, or prolonged web sessions on entertainment websites can be attributed to the counterproductive and unplanned behaviour. In addition to affective states relating to emotions, experiencing stress, and anxiety, failures of self-regulatory behaviour can be related to other possible circumstances, such as a lack of motivation to engage in certain activities, perceived limitations in one's cognitive capabilities required by the learning task, and/or poor metacognitive skills.

3.3.3 Trace data and self-regulation as a digital footprint

Data related to learners' self-regulation can be gathered using self-reporting (e.g. questionnaires) and digital behaviour traces (or simply traces). Behaviour traces are predominantly based on clickstream data, learners' interactions with the learning management system and its content, a pathway to complete a chosen course and data regarding social interactions between learners. The choice to select variables for analysis is often driven by data availability; course instructors and researchers usually have access to data generated within the boundaries of learning management systems, or provided by course platforms, such as Coursera or EdX (in case if course content is hosted on an external platform). However, only tracking data inside learning management systems pose restrictions on assessing the broad scope of SRL, without taking into account the self-regulatory processes beyond any given course platform.

Research that handles data beyond MOOC environments has begun to emerge. For example, Chen, Davis, Lin, Hauff and Houben (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. In addition to demonstrating the ability to collect different types of data beyond MOOC learning environments in their exploratory analysis the authors were able to estimate MOOC participants' age distribution and to classify their gender based on Twitter data. This was achieved with a 78.3% accuracy. They were able to identify the most frequent job titles and skills to appear listed in participants' profiles, based on LinkedIn data. Further, their study revealed that participants demonstrated expertise-dispensing behaviour while accessing the programme. For instance, participants demonstrated an increased prevalence of answers posted over questions on stackoverflow.com, as well as increasing contributions to github.com (Chen et al., 2016, pp. 20-23). Pérez-Sanagustín, Sharma, Pérez-Álvarez, Maldonado-Mahauad and Broisin's exploratory study (2019) extended the scope of available data by including learners' interactions with a broader scope of web resources, such as social media, news, and search engines. Based on an exploration of 572 learners from four MOOCs, the authors found that additional data can contribute to the prediction of learners' grades on their online courses.

It seems reasonable to assume that self-regulated learning occurs not in isolation (not only inside learning management systems), but also may occurs in a broader context, across interactions with a range of resources, which may not directly be related to learning contexts. Behaviour traces from such interactions can also be utilised to contribute to the assessment of SRL. Multimodal learning analytics used in offline settings with video recording and sensors as additional data sources (see, for example, Järvelä, Malmberg, Haataja, Sobocinski and Kirschner, 2019; Järvelä, Gašević, Seppänen, Pechenizkiy and Kirschner, 2020) represent one impressive example.

3.3.4 Characteristics of traces of self-regulation

To characterise behavioural traces of self-regulation in online learning, a starting point can be set at a single event of an activity performed by a learner in their learning environment, and in the broader field's context, their all internet activity. Due to the nature of online learning, whereby a significant part of the online course is, naturally, provided online (in addition to instructions, reading materials and secondary reference resources are also often presented online), the main aim is to track events in learners' browser environments. Learners create actions in their web browsers: they open tabs in their browser windows, visit URLs, switch between opened tabs, switch between their browser and other installed software. Each of these actions can be considered as a single point of activity. For example, a learner might open an online course website on the MOOC platform 'edx.org' in their browser, spend one minute on this URL without interruption, and might then open another website, e.g. 'discover.durham.ac.uk', spending another minute on this second page. This sequential activity consists of two events. In case of visiting the 'edx.org' domain and 'discover.durham.ac.uk', both activities can be considered academic, denoting behavioural engagement with learning. The learner spends, first, time on their course website (providing that the learner has indicated that their course is hosted on 'edx.org') and, second, time on a learning-related resource. In the latter case, the assumption that this web resource is related to learning is based on the top-level name of the visited domain — '.ac.uk'.

With the obvious exception of traces drawn from single events, it is essential to characterise traces as sequences of events. Sequential events are taken together to form time-series data. It is assumed that sequential time series data can provide insight into learners' interactions with learning and learning-related environments, alongside the underlying processes involved in self-regulation in online learning. In accordance with technological determinism (i.e. a set of claims regarding the influential role of technology on society), the characteristics of media and web platforms influence learners' behaviour to some extent (Oliver, 2011). Internet activity can be characterised by what philosopher Marshall McLuhan and futurist

Alvin Toffler have described as fragmented or 'clip' culture. Applying this to human actions in web environments, users often do not stick to one resource for an extended period of time and frequently switch between internet pages. Thus, in the fast processing, fragmented, and rapidly changing, web environments, it is reasonable to assume chaotic, frequent and fast-changing behaviour.

In addition, web navigation happens across browser windows and in single window tabs. Some learners may use several different browsers concurrently, alongside additional software installed on their machines. However, using two or more different browsers concurrently is assumed to be relatively uncommon, while software usage can be characterised as being much less destructive, by comparison to he web environment. It should be also acknowledged that online learners will not necessarily spend all of their time in front of their laptop or other electronic devices and might be distracted by other events when their browsers are open. Learners could even leave their electronic devices with opened web pages in idle mode. Traces captured during the mentioned scenarios should be considered as noise, and their collection should be avoided.

To conclude this chapter, several approaches can be applied to measure self-regulatory skills, including implementing traditional self-report questionnaires, digital traces, or combinations of both. As online learning happens in online environments, learners' interactions with their environment result in specific digital footprints. These footprints (i.e. traces) include single events, sequences of activities, and patterns. Learners apply a broad range of actions prior, during, and after the learning process, and it is possible to trace such actions. Distinct approaches to assessing self-regulation can be consolidated into one systematic operationalisation of self-regulation in online learning through several approaches, including self-report and behavioural measures of affective, cognitive, metacognitive, and motivational components, self-regulated learning strategies and processes at macro and and micro levels of detail (and different levels of granularity).

4 | Development and Compensation of Self-Regulation

4.1 Developmental activities

Based on the conceptualisation and operationalisation of self-regulation in online learning, learners acquire their competency in self-regulation through developmental activities that include engaging in self-regulatory behaviours. Previous theoretical stances tend to broadly agree that self-regulation in online learning is a skill that can be developed, compensated for, and ultimately observed. Self-regulation includes cyclical sequential phases: planning, monitoring and self-control, and self-evaluation. Planning includes a survey of available resources, goal setting, and the development of strategic and tactical intentions. Monitoring entails the observation of performed behaviour and its consequences; self-control consists of selecting behaviour that is conducive to achieving set goals and avoid behaviour that distracts from achieving them. Self-evaluation includes a survey of performed actions and contrasting outcomes with set goals. In this chapter, developmental activities and compensatory strategies to help online learners to support their self-regulatory skills are discussed, ultimately informing the development of an intervention with the aim to support online learners.

In order to support learners' involvement in exercising self-regulation, learners need to be provided with an environment in which they can engage in self-regulation, supporting each phase underpinning SRL, including planning, monitoring, and self-evaluation. Providing learners with the opportunity for experiencing mastery should increase their self-efficacy (Bandura, 1994), one of the central elements of self-regulated learning that affects students' learning, motivation, and achievement (Schunk and Usher, 2011, p. 294). Providing learners with coping models helps them to acquire their SRL competency (Zimmerman, 2000). This especially applies to learners experiencing academic difficulties. As noted by Schunk and Usher (2011), in contrast to mastery models, coping models help learners who initially experience difficulty but, through effort, persistence, and the use of effective strategies are able to improve their performance and eventually become successful in their self-regulatory effort (Schunk and Usher, 2011, p. 294). In terms of practical implementations, pedagogical mechanisms, such as providing modelling, feedback, and instructional support, have been shown to help learners to develop their self-regulatory skills (Hadwin, Järvelä and Miller, 2018). Therefore, it is assumed that practising self-regulation helps learners developing self-regulatory skills, and it can be supported by providing learners with tools to foster the development of self-regulation. This support can be reduced over time, as, based on Vygotsky's zone of proximal development, scaffolding helps to develop learners' ability to progress independently over time.

Several attempts have been made to design intervention options that foster the development of online learners' self-regulatory skills. Several systematic reviews report recent advances in research devoted to measuring and supporting learners' self-regulation in online learning environments (Pérez-Álvarez, Maldonado-Mahauad and Pérez-Sanagustín, 2018; Wong et al., 2019; Araka, Maina, Gitonga and Oboko, 2020; Viberg, Khalil and Baars, 2020), while one meta-analysis has been conducted, evaluating the impact of self-regulated learning scaffolds on academic performance in computer-based learning environments (Zheng, 2016). Despite differences in the approaches taken to conduct these reviews, their findings agree on the principle that the majority of tools designed to support learners' self-regulation are focused on providing support by equipping learners with the assistance for goal setting, receiving feedback on behaviour and self-evaluation. Despite the variability of the available tools focusing on supporting self-regulated learning, the majority of the instruments aim to measure SRL to classify learners according to their levels of self-regulation, and the need to increase the utilisation of support mechanisms to foster learners' SRL was indicated in the reviews.

These systematic reviews consider a range of options to support SRL in MOOCs, for example, standalone systems such as OnTask learning, a platform that provides feedback through personalised messages (Pardo et al., 2018; Pardo, Jovanovic, Dawson, Gašević and Mirriahi, 2019); mobile apps, e.g.

MyLearningMentor, designed to provide MOOC learners with personalised planning instruments (Alario-Hoyos, Estévez-Ayres, Pérez-Sanagustín, Leony and Kloos, 2015), and LearnTracker which records learning time and provides mobile notifications to foster learners' reflective practice (Tabuenca, Kalz, Drachsler and Specht, 2015); virtual companions, such as one proposed by Sambe, Bouchet and Labat's (2018), which was designed to provide metacognitive prompts and visualisations of learning indicators; widgets that integrate with online courses, such as the Learning Tracker widget, a predefined widget bundle which aims to support SRL by providing goal-oriented feedback to encourage learners' self-reflection (Davis, Chen, Jivet, Hauff and Houben, 2016); virtual learning environments, such as MetaTutor, a virtual learning environment designed to detect, track, model, and foster learners' self-regulation with the focus on providing learners with help setting goals (Azevedo, Moos, Johnson and Chauncey, 2010); finally, extensions to web browsers. For example, nStudy that is equipped with the function to assemble web pages as learning analytics based on learners' behaviour (Winne and Hadwin, 2013; Winne, Nesbit and Popowich, 2017), and NoteMyProgress that 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, Maldonado-Mahauad, Sapunar-Opazo and Pérez-Sanagustín, 2017).

Reviewed instruments indicate the heterogeneous distribution of the functional orientations of currently available intervention tools. For example, Pérez-Álvarez, Maldonado-Mahauad and Pérez-Sanagustín's survey of intervention designs (2018) identified 22 tools aimed to support self-regulated learning. The most common features of functionality identified in these tools were: visualisation (14 of the 22 evaluated tools had this functionality), collaboration (11), input forms (10), recommendation (9), social comparison (5), text feedback (4) and interactivity (4). Among these 22 tools, 7 were designated to support SRL in the context of MOOCs. These seven tools were assigned to support learners' goal-setting, self-monitoring of one's procrastinatory behaviour, and to enable the self-evaluation of the learner's progress towards their set goals (Pérez-Álvarez et al., 2018, p. 23).

Overall, three major forms of SRL support have dominated research to date: visualisations to raise learners' self-awareness, feedback with prompts to stimulate reflection on learning experiences, and providing recommendations. Experimental evaluation of interventions have been discussed relatively rarely, with evaluation discussion identified in only 8% of examined studies in one of the reviews (Viberg et al., 2020, p. 529). In addition, the results of a meta-analysis of 29 studies published between 2004 and 2015, with a total sample size of 2648 learners indicates, on average, a medium positive effect ($ES = 0.438$) of SRL scaffolding intervention on academic performance (Zheng, 2016, p. 197). Also, simply proving supporting tools is not enough, as in online learning environments learners also need to be taught how to utilise the support, and the support should be tailored to learners' behaviour, as discussed by Wong et al. (2019, p. 369).

Although, on average, tools introduced to support SRL have been shown to have a positive effect on learners' self-regulation, interventions are often disparate, consisting of either measuring components, prompts, messages with feedback on behaviour, or visualisations. Only a small proportion of available interventions consist of several intervention options that are able to work in combination, adapting to individual learners' needs. While these tools aim to support learners' self-regulation, their implementation within learning environments may exclude learning with low self-regulatory skills. It is, therefore, imperative to seek out ways to overcome this issue. Also, the majority of these tools rely on specific courses and learning management systems, where the tools are supposed to be implemented, creating limitations in their transferability to other MOOCs and LMSs. However, solutions such as mobile apps (e.g. LearnTracker), extensions to browsers (e.g. NoteMyProgress, nStudy), and superstructure intervention systems (e.g. OnTask learning) provide more flexibility in terms of the application of self-regulation enhancement software to different contexts and different MOOC platforms, regardless of whether learners are enrolled in a particular course or are using a particular learning platform.

4.2 Compensatory strategies

Providing learners with opportunities to exercise self-regulation generally assumes learners' willingness to engage in developmental activities. However, it can be assumed that learners require a certain level of self-regulation even prior to engaging in developmental activities. Therefore, a lack of self-regulatory skills may result in limited effects on learners' SRL development. In such cases, an intervention can be utilised as a compensatory mechanism to support the skill targeted for development. Compensatory strategies can be utilised when learners experience issues with self-regulation, especially in the case of the failure of self-regulatory behaviour (as described in Section 3.2.2). Consequently, compensatory strategies that support learners' SRL can be applied, which should result in changes in learners' behaviour (given the absence of detectable changes in skill development).

As shown in the overview of mentioned earlier tools, variants of compensatory strategies were present to support SRL, such as the adaptive prompts offered in the pedagogical agent MetaTutor. Assessed across 40 students, Bouchet, Harley and Azevedo's (2013) evaluation of MetaTutor's adaptive self-regulated prompting strategies demonstrated that learners who received (1) frequency-based adaptive prompting and (2) frequency and quality-based adaptive prompting strategies gave more effort to self-monitoring and utilisation of SRL strategies, with a corresponding increase in learning gains when compared to learners who received the non-adaptive prompting strategies of the tool (Bouchet, Harley and Azevedo, 2013, p. 818). Lallé, Conati, Azevedo, Mudrick and Taub's (2017) evaluation of MetaTutor employed self-report and behavioural data drawn from 28 college students. This study focused on the relationship between learning gains and learners' compliance with prompts. In addition to questionnaire responses and behavioural traces regarding pages viewed and performed interactions with MetaTutor, these data was supplemented by information about gaze fixations on learning pages, derived using eye-tracking devices. This study demonstrated that students' compliance with prompts designed to support learners' self-regulation influenced learning gains. However, not all types of prompts were associated with learning gains. For example, prompts related to metacognitive monitoring processes seem to have not affected students' achieving learning gains (Lallé, Conati, Azevedo, Mudrick and Taub, 2017, p. 126). Despite optimism surrounding the role of adaptive compensatory assistance implemented as the prompting strategy, these results should be taken with caution due to the limited sample size of existing studies, the short learning sessions (up to 90 minutes each) used in evaluations, and a lack of clarity regarding potential long-term effects of the tool.

In addition to content of interventions, time variability is crucial to compensatory strategies to support learners' self-regulatory skills. In their study on the effect of self-directed metacognitive prompts to support SRL, Bannert, Sonnenberg, Mengelkamp and Pieger (2015) highlighted that time aspects allow more precise scaffolds to the learning process to be built (Bannert et al., 2015, p. 295). The authors further claimed that self-directed metacognitive prompts have a long-term effect on learning performance, and can be transferred to different learning tasks:

> Above all, this result is promising because it is a first indication that metacognitive prompts may have not only short-term effects but effects that are maintained for several weeks. One explanation may be that the prompts not only promoted a better regulation of the learning process but that these learning activities were maintained and transferred to other learning contents that were presented within the identical learning environment. (Bannert et al., 2015, p. 303)

Taken together, an intervention that includes compensatory strategies can be more effectively utilised to support learners' self-regulation: the intervention will, then, be capable of meeting individual learners' needs in different contexts. To compensate for a lack of self-regulatory skills, it is important to identify periods when they are most needed. The capacity to correctly identify situations in which learners are in need of SRL support is as important as the intervention option itself. This functionality should help to maintain learners' responsiveness to intervention over time. An intervention equipped with this functionality is known as adaptive assistance, whereby the intervention is triggered by recorded behaviour. In the case of SRL, this could be the detected failure of self-regulatory behaviour. Therefore, it is crucial to detect the failure of self-regulatory behaviour, which is a precursor of the requirement for adaptive assistance.

4.3 Adaptive assistance and behaviour change

Adaptive assistance is applied in intervention designs in both educational and broad social sciences settings. Adaptive scaffolding has been effectively used to foster self-regulation (see, for example, Azevedo, Cromley, Winters, Moos and Greene, 2005; Duffy and Azevedo, 2015) and to enhance learning (see, for example, Poitras and Lajoie, 2014). Furthermore, a variety of forms of adaptive assistance have become increasingly common in medical research and mobile health applications, facilitated by the omnipresence of smartphones and other smart devices as tools to prevent, assist or replace medical treatments. In healthcare settings, research on adaptive assistance (also known as Just-in-time Adaptive Interventions (JITAI)) is supported by recent advances in intervention design, evaluation, and reporting methodologies (see, for example, the Multiphase Optimization Strategy (MOST) framework to design interventions, described in Collins, 2018; Micro Randomised Trial (MRT) to evaluate interventions, described in Klasnja et al., 2015; guidelines for reporting of health interventions using mobile phones, described in Agarwal et al., 2016).

In most cases, JITAI consist of a range of treatment messages, including behavioural, cognitive, and motivational messages, where behaviour change is considered to be the measurable outcome. These intervention messages are based on several components: (1) decision points (i.e. whether a set of pre-specified conditions to deliver an intervention are met), (2) intervention options (i.e. which intervention option should be delivered), (3) tailoring variables (i.e. how the chosen intervention option should be modified to a particular recipient), and (4) decision rules (i.e. whether an intervention should be delivered or not), as noted in the framework for adaptive preventive interventions by Collins, Murphy and Bierman (2004) and in research on key components and design principles for ongoing health behaviour support by Nahum-Shani et al. (2018). These advances in mHealth research can be utilised in educational settings to aid research on adaptive assistance.

A variety of intervention options which have been applied in medical studies have pose a challenge of comparability of their mechanisms of change and their effectiveness. To overcome this challenge, several classification systems of intervention options have been developed to systematise the reporting of behaviour change interventions. To mitigate discrepancies between classification systems, the Behaviour Change Technique (BCT) taxonomy of 93 hierarchically clustered techniques (Michie et al., 2013) was developed, aiding researchers with an agreed tool for reporting behaviour change interventions. The development of this taxonomy involved 14 experts in behaviour change who labelled and provided definitions of 124 BCTs from six previously published classification systems. Next, another cohort of 18 experts combined BCTs according to their similarity of active intervention mechanisms. Finally, inter-rater agreement between six researchers resulted in 93 agreed BCTs, included in the taxonomy. Currently, this taxonomy is widely used to report findings in studies relating to behaviour change, as the basis for compendia (see, for example, the description of the compendium of self-enactable techniques in Knittle et al., 2020), and advanced ontologies (for example, not only expert generated ontologies but those that incorporate user feedback and data-driven methods, for more details see discussion in Norris, Finnerty, Hastings, Stokes and Michie, 2019).

Behaviour change techniques (as narrow definitions of intervention components) can be more broadly categorised by indicating the main function of each intervention option. Experts have identified nine intervention functions, where each BCT can serve one or several functions. Among the listed functions and their definitions are: Education, Persuasion, Incentivisation, Coercion, Training, Restriction, Environmental restructuring, Modelling, and Enablement. Definitions of the functions are summarised in Table 4.1 (extracted from Michie, van Stralen and West, 2011, p. 7).

Regarding adaptive assistance and its development, research on BCTs can be utilised in two key ways. First, the taxonomy can be applied to aid reporting the intervention options integrated into the adaptive assistance model, in accordance with the predetermined classification system given in the taxonomy. Second, in addition to the proven effective developmental and compensatory intervention options described in research in educational settings (covered in the previous two

Table 4.1 Functions of intervention components and their definitions.

Function	Definition
Education	Increasing knowledge or understanding
Persuasion	Using communication to induce positive or negative feelings or stimulate action
Incentivisation	Creating expectation of reward
Coercion	Creating expectation of punishment or cost
Training	Imparting skills
Restriction	Using rules to reduce the opportunity to engage in the target behaviour (or to increase the target behaviour by reducing the opportunity to engage in competing behaviours)
Environmental restructuring	Changing the physical or social context
Modelling	Providing an example for people to aspire to or imitate
Enablement	Increasing means/reducing barriers to increase capability or opportunity (capability beyond education and training; opportunity beyond environmental restructuring)

subsections), the behaviour change techniques applied in the field of medical research (proven in this context), can perhaps benefit the variety of intervention content options to support self-regulated learning. Thus, in addition to supporting research evaluators to describe intervention options, share expertise across domains, and analyse their effects for comparability, this taxonomy of BCTs can be utilised not only to describe existing intervention options, but can be leveraged in the construction of a novel intervention that has a potential to change learners' behaviour in a desired way in educational settings. For this purpose the 'Behaviour change wheel' framework (Michie, Atkins and West, 2014; Michie et al., 2011) which was developed with the aim to improve evidence-based practice, its design, and implementation in behavioural science can be utilised.

This approach augments traditional approaches to educational intervention development, which is often guided by the available theories; intervention options that are outside of the scope of established theories are often ignored by intervention designers. This means that intervention options that lack a direct link to supporting solid theoretical stance in theory of SRL have a chance to be neglected by intervention designers and evaluators. It seems possible that intervention options demonstrated its power in other areas of application, and reported in behaviour change research studies can be brought to educational settings; learners would benefit from receiving an intervention aimed to change their behaviour in the course of practising self-regulatory actions. To support the claim above, two examples will be provided in the next two paragraphs.

Research in the area of behaviour change is supported by different theoretical stances. These approaches are varied from the classical Pavlovian conditioning model to theories that lie at the core of models of self-regulated learning, such as socio-cognitive and self-efficacy theories[1]. For instance, providing learners with feedback on behaviour toward their goals would encourage self-reflection and provide an opportunity for mastery experience. According to the taxonomy of BCTs, this intervention option can be labelled as the 'Feedback on behaviour' behaviour change technique. This technique is widely utilised as an intervention option in a variety of tools that aim to support SRL, as noted in the previous subsections.

In addition to the classification of intervention options provided above, another useful application of the taxonomy of behaviour change techniques is in its potential to inform new intervention developments. For instance, a behaviour change technique labelled 'Body changes' in the taxonomy refers to intervention options defined as actions aimed to 'alter body structure, functioning or support directly to facilitate behavior change' (Michie et al., 2013, see Table 3 in the electronic supplementary materials, p. 17). An example of this BCT was provided as follows: 'Prompt strength training, relaxation training or provide assisted aids (e.g. a hearing aid)'. This option can be utilised as an intervention option, and a more differentiated view is needed here. It can be pointed out that this 'Body changes' BCT and intervention options related to this technique were effectively applied to promote physical activity in healthcare research. For example, an intervention that included the 'Body Changes' BCT demonstrated an effect on behaviour change in terms of positive impact on physical activity (O'Dwyer, Monaghan, Moran, O'Shea and Wilson, 2017). Physical activity, in turn, is usually associated with a positive impact on emotional well-being (e.g. Saxena, Van Ommeren, Tang and Armstrong, 2005) and cognitive abilities (e.g. Fernandes, Arida and Gomez-Pinilla, 2017). Here, the 'mechanism of change' flow brings this BCT back to self-regulated learning, as learners' affective and cognitive

[1]For coverage of a range of approaches applied in behaviour change research, see the compendium of behaviour change theories in Michie et al., 2014; for discussions on behaviour change from an interdisciplinary perspective see Christmas, Michie and West, 2015

components are important parts of models of self-regulated learning. The positive impact on these two components of SRL should, therefore, positively impact learners' self-regulation as a whole construct. Thus, it can be assumed that some less obvious intervention options may have the potential to support learners' self-regulation. Therefore, intervention options based on the taxonomy of behaviour change techniques provided within adaptive assistance could have a positive impact on learners' self-regulation, however, not all of them would likely be effective, and selecting the most suitable options from a broad range of BCTs is needed, based on a broad conceptualisation and operationalisation of self-regulated learning.

4.4 The interplay of approaches to learning

Self-regulated learning can be studied from different disciplinary perspectives, for example, through the lens of developmental psychology with the focus on its basic cognitive abilities, such as working memory, focused attention, and inhibitory control; or through the lens of educational psychology with the focus on higher-level cognitive abilities, such as reasoning, problem-solving, and planning. In addition, self-regulation in learning can be viewed from a range of approaches to learning, including behavioural, cognitive and constructivist, and their intersections. As previously noted (Section 1.3, and Chapter 2), self-regulation is acquired through developmental activities, and its levels determined by the involvement of learners' abilities and resources. Learning, viewed as as the product of latent changes (supported by cognitivists' theories), and resulting from learners' mental activity (as supported by constructivists) can be supported by ideas rooted in behaviour analysis. As noted in Markovits and Weinstein's perspective paper on '*npj Science of Learning*' (2018), the fields of cognitive psychology and behaviour analysis share the same aim, despite differences in theoretical stances. Their efforts often reach similar conclusions, and both fields would benefit from collaboration:

> The main difference between cognitive and behavioral research is that cognitive psychologists seek to explain the specific processes in the mind that give rise to observed behaviors (here, better performance on memory

> tests after generation or retrieval practice than after passive re-reading) while behavioralists focus on manipulating the environment to produce those observed behaviors. Regardless of these differences, both fields want to improve educational outcomes for students through effective pedagogical techniques. To the extent that the two fields appear to be investigating the same types of educational interventions, a more open dialog would be more efficient for the advancement of both fields. (Markovits and Weinstein, 2018, p. 3)

Changing learners' behaviour and directing learners towards self-regulatory activities (to practice self-regulation) can work similarly to nudging. Nudging people to perform certain behaviours has been proven to have an effect on achieving desired behaviour in applied domains, such as improving clinical trial enrolment (VanEpps, Volpp and Halpern, 2016), increasing citizenship application rates among low-income immigrants (Hotard, Lawrence, Laitin and Hainmueller, 2019), or nudging farmers to use fertilisers by providing them with a modest time-limited discount that results in higher welfare farming practices, compared to providing sizeable subsidies or no-intervention policies (Duflo, Kremer and Robinson, 2011). In education, several studies have claimed that providing school meals increases school attendance across rural communities in developing countries (see, for example, Vermeersch and Kremer, 2004; Afridi, 2011, Alderman, Gilligan and Lehrer, 2012). However, changing behaviour does not only rely on nudges; behaviour change can be achieved through other forms of communication, for example, prompts that trigger learners' metacognition that, in turn, result in learners' behaviour change. Different forms of triggers should initially help to position learners in environments in which they can practice self-regulation. This practice should, then, help to reinforce their self-regulatory skills and lead to some form of habit formation (speculatively speaking).

Behavioural approaches can be utilised as to build an intervention that triggers the activation of the learner's internal processes. This could be compared to setting an alarm to wake up in the morning. The alarm, in this context, is a helpful irritant that catalyses the brain's transition from sleep to wakefulness. Indeed, not every learner who wakes up on time will go to a class, or learn something that day, but this nonetheless create an opportunity for learners' improvement. Similarly, the components responsible for self-regulation during learning, such as affective, cognitive, metacognitive, and motivational components, can be triggered by providing timely interventions, but might not provide immediate results in observable behavioural changes. Given differentiation between learners, distinct learning tasks require varying levels of effort, and situational characteristics are, naturally, varied. Therefore, assistance should be adaptive.

4.5 Virtual learning assistant

An effective SRL intervention should include several features, as discussed in previous sections. This intervention should encourage learners to set learning goals and to survey required resources to achieve these goals; to record progress toward the learning set goals and to self-monitor; to compare achieved results toward set goals and to resist engaging in competing activities which are unrelated to set goals. Finally, and most importantly, this intervention should adaptively provide learners with the opportunity to exercise self-regulation at the most suitable time.

To support learners to engage in self-regulation when involved in online learning, an adaptive online learning assistant was developed. The main features of this tool are outlined in this section. This tool consists of a web application with a user interface that enables goal setting, progress monitoring and self-evaluation, a web browser extension to collect trace data and display notifications, and a SQL database with trace data. The web application of the tool consists of several components that allow learners to interact with the tool. Figure 4.1 illustrates the goal setting interface, where learners can indicate one or several goals in terms of an online course (or courses) they wish to complete.

As shown in Figure 4.1, learners can both indicate a start date and set a deadline for goals, indicating the time range required for the completion of a given course. Learners are encouraged to provide information regarding a discussion forum (if there is one linked to the course), the proportion of the course which has been completed to date (this can be adjusted at a later stage), the intended time commitment toward the goal, and to indicate the course name, which will appear in their list of added courses (learning goals).

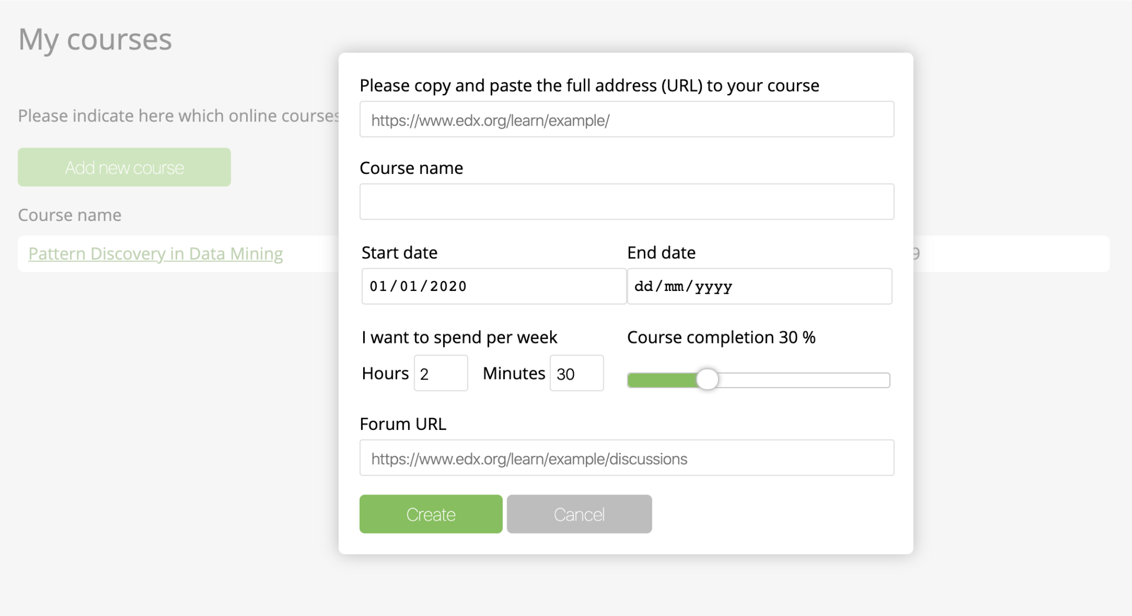


Figure 4.1 Example of the user interface to support the goal setting and goal adjustment functionality of the tool.

The next component of the web application includes a self-monitoring function — an example of the user interface is illustrated in Figure 4.2. This page is presented to learners alongside statistics indicating their recorded behaviour (behaviour recorded with the web browser extension of the tool). The summary of time spent by a learner on each of online web domains is calculated for a current day and a current week and displayed in real time to learners, hence providing feedback on their behaviour.

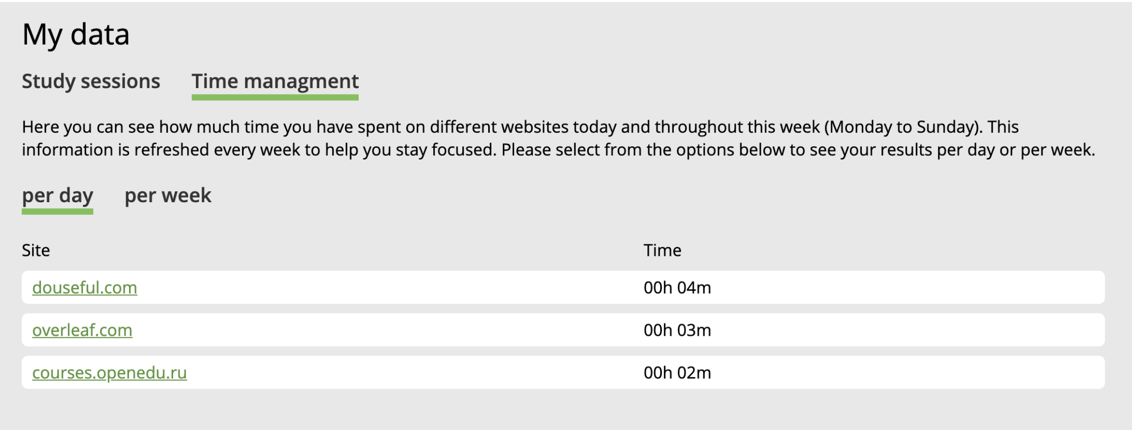


Figure 4.2 Example of the user interface to support the self-monitoring of behaviour functionality of the tool.

Another key component of the web application is the self-evaluation functionality. An example of the user interface for this component is provided in Figure 4.3.

This dashboard provides learners with a visualisation of summary statistics of time committed by a learner to their indicated course (their learning goal). The desired time is indicated next to recorded and displayed summary statistics, allowing the learner to evaluate their progress toward the goal, entered during the goal-setting stage.

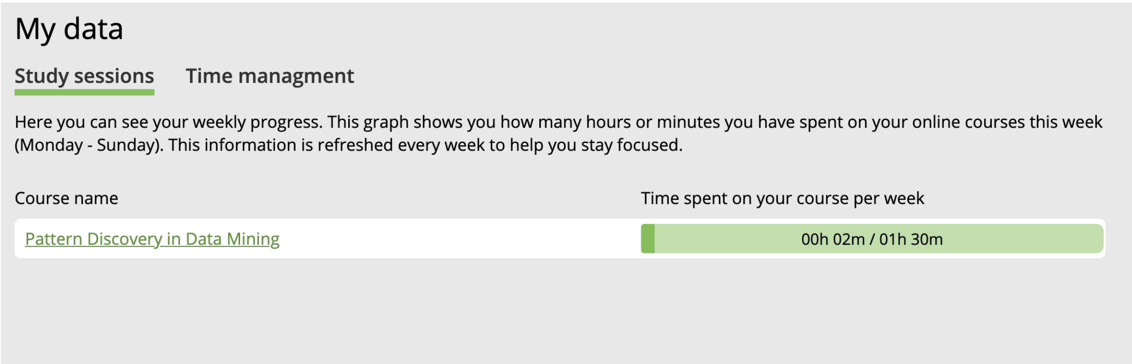


Figure 4.3 Example of the user interface to support the self-evaluation functionality of the tool.

To provide learners with a compensatory mechanism, an additional functional was developed: pop-up messages that appear in learners' web-browser environments, in response to learners' behaviour. An example of such pop-up messages is illustrated in Figure 4.4.

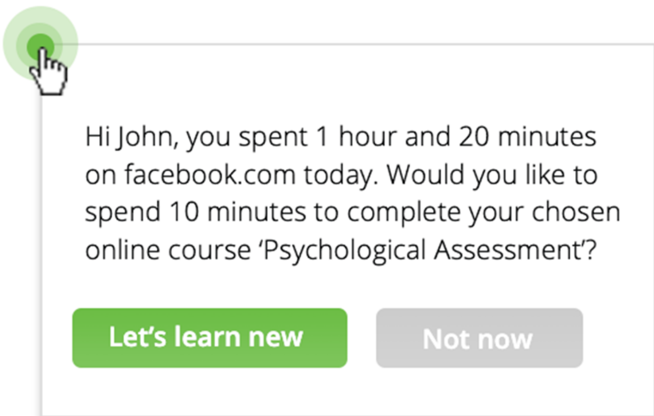


Figure 4.4 Example of the pop-up notification functionality of the tool.

The appearance of these pop-up messages in learners' web browser windows is based on pre-specified rules which can be adjusted by learners during their usage of the tool. Based on the operationalisation of SRL, the pre-specified decision rules were selected based on apparent lapses of SRL. Therefore, their occurrence signals the need for self-regulatory assistance. Therefore, the task of regulating the intensity of assistance is partly shared with a learner by allowing personalisation of decisions regarding when the assistance occurs. Figures 4.5, 4.6, 4.7 illustrate dashboards where learners can create lists of websites that are considered in the decision rules.

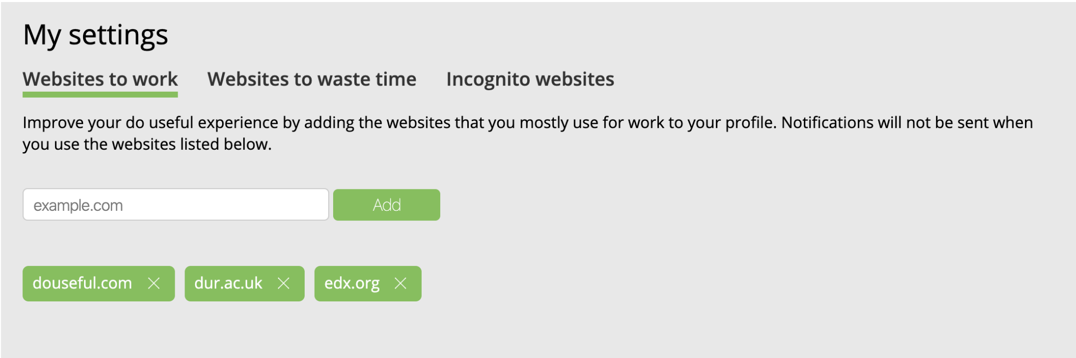


Figure 4.5 Example of dashboards to classify URLs: websites to work.

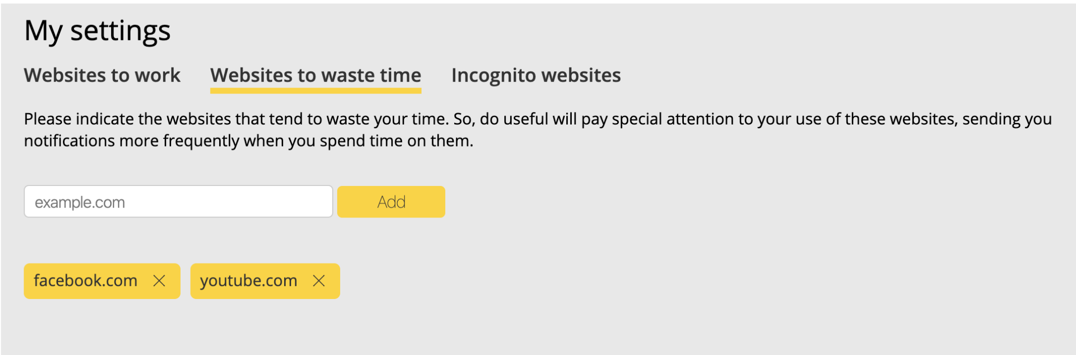


Figure 4.6 Example of dashboards to classify URLs: time wasting websites.

Figure 4.7 Example of dashboards to classify URLs: incognito websites.

Based on the operationalisation of self-regulation in online learning, behaviour which is likely to represent a problem in self-regulation can be expressed in excessive time spent on resources that are not related to the indicated learning goals. This time can be calculated based on time captured within the browser extension installed by learners to their web browsers. Hence, the failure of self-regulatory behaviour can be traced through reliance on learners' behaviour. When the failure of self-regulatory behaviour occurs, an intervention to prevent procrastinatory behaviour can be provided to encourage a shift in learners' behaviour. To achieve this, behaviour tracking functionality was implemented in the tool. The Figure 4.8 provides a schematic summary of the tracking components of the virtual assistant and a hypothetical scenario of a learner's behaviour together with actions taken by the adaptive assistance component of the virtual assistant triggered by the learner's behaviour.

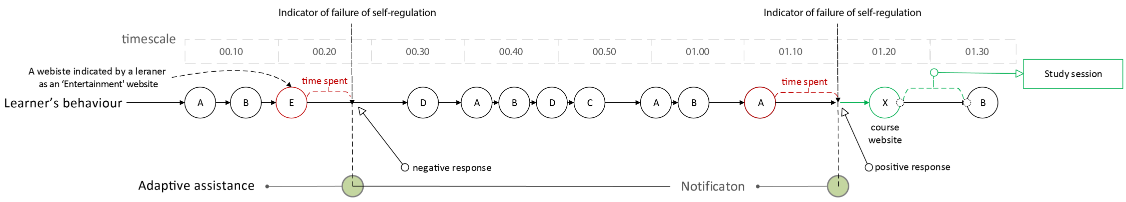


Figure 4.8 Schematic illustration of a hypothetical learner's behaviour and an example of the compensatory functionality of the tool as the response to observed behaviour and the occurrence of the failure of self-regulatory behaviour.

The adaptive assistance component of the virtual assistant proposed here is based on several distinct templates with textual content. The expectation is to help learners to not simply change their immediate actions and to compensate for lack of self-regulatory skills, but to provide them with a more long-term effect in terms of self-regulatory skill development. The content of the pop-up messages implemented in the adaptive assistance component is determined by carefully considered models of SRL, based on the examination of research relating to the effectiveness of a number of interventions, and the selection of BCTs, which provide additional intervention options. The application of BCTs should support learners' engagement with a given learning task and to exercise self-regulatory phases of self-regulated learning. Overall, this approach, providing learners with adaptive assistance, is illustrated in Figure 4.9.

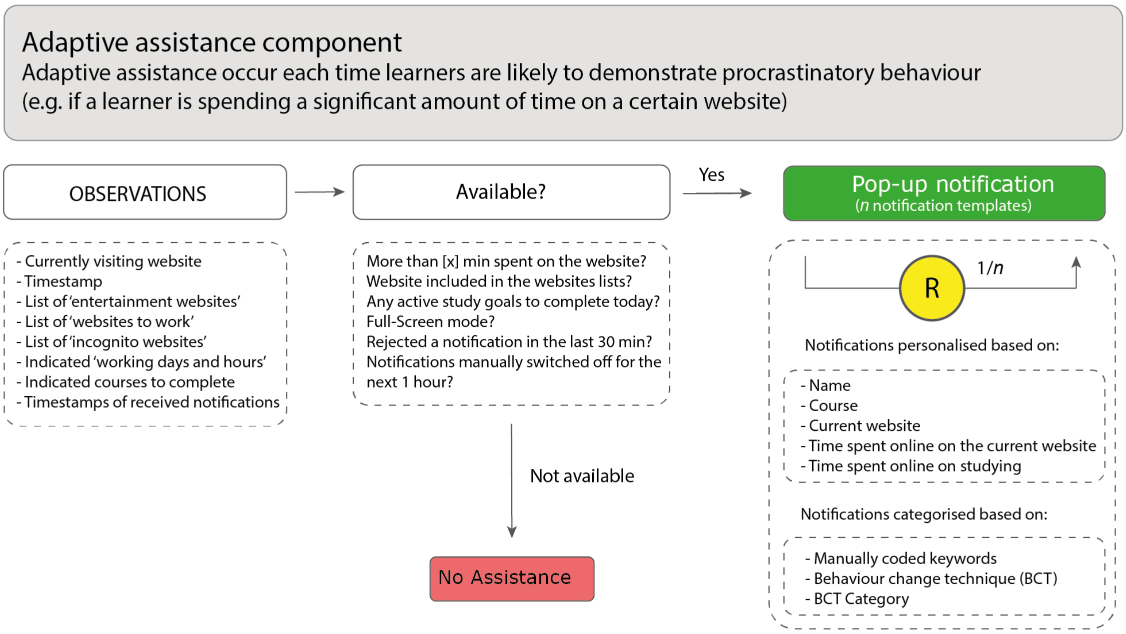


Figure 4.9 Schematic illustration of the adaptive assistance component and its decision rules.

4.6 Research questions and hypotheses

The main research question to be examined in the study is the assumption that 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, that can be operationalised via analysing behavioural traces. The developmental and compensatory shifts in learners' self-regulatory skills are determined by learners' individual differences in cognitive and non-cognitive variables.

The main research questions to be address are as follows:

Question 1. Can the development of self-regulatory skills in learners be facilitated by adaptive online learning assistance?

Question 2. Can a lack of self-regulatory skills in learners be compensated by providing adaptive online learning assistance?

Question 3. What is the role of individual differences in the compensatory and developmental shift in self-regulation of learning?

The aim of the subsequent study is to evaluate the effectiveness of the adaptive assistance intervention delivered in the web browser environment, with the intent to improve learners' self-regulation.

5 | Methods

5.1 Summary

This chapter reports on a study to evaluate the effects of the adaptive online learning assistant, which aims to support online learners to (a) compensate for potential deficits in self-regulation, and (b) to ultimately facilitate the development of their self-regulatory skills. This study incorporates a combination of behavioural and self-report measures to evaluate the assistant. Participants who voluntarily created an account on the assistant's website, installed the extension to their web-browser, and then indicated that they were attempting to complete an online course were randomised into one of two experimental conditions. In both conditions, participants had access to a constant intervention component. The constant intervention component consisted of online instruments for goal setting, self-monitoring of one's recorded behaviour and self-evaluation towards the indicated goals. Learners allocated to the control condition had access to the constant intervention component only. Participants in the intervention group received adaptive assistance (which was implemented in the form of pop-up on-screen notification messages, or simply notifications), while also having the option to utilise the constant intervention component.

Prior to engaging in their respective online course, each participant was asked to respond to a web-based questionnaire which aimed to ascertain participants' demographics, levels of self-regulated learning (baseline or pre-intervention measure), and individual differences in personality traits. After a period of 30 days, whilst working on their online course, the self-regulation questionnaire was re-administered (post-intervention measure). Figure 5.1 provides a schematic illustration of the schedule of enrolment, intervention, and data collection timeline.

The primary outcome measures were: changes in self-report levels of self-regulation and changes of the proportion of actual time dedicated to learning (the indicated online course and web-resources categorised as educational).

	STUDY PERIOD						
	Enrolment	Allocation	Post-allocation				Close-out
TIMEPOINT	week (w) 0	w0	w1	w2	w3	w4	day 30
ENROLMENT:							
Eligibility screen	x						
Information sheet	x						
Informed consent	x						
Randomisation		x					
INTERVENTIONS:							
Intervention group with adaptive assistance and constant component							
Control group with constant component							
ASSESSMENTS:							
OSRLQ		x					x
IPIP		x					
Trace data							

OSRLQ – Online Self-Regulated Learning Questionnaire
IPIP – International Personality Item Pool questionnaire

Figure 5.1 Schematic illustration of the schedule of enrolment, intervention, and data collection.

Secondary outcome measures included: the extent to which the proportion of actual time dedicated to selected categories of web-resources deviate from the total time spent online, and learners' online behaviour following a decision point indicated the need to provide an intervention. One set of analyses assessed the effects of the adaptive assistance intervention by the virtual assistant on learners' levels of self-report self-regulation scores and online behaviours. In another set of analyses the role that individual differences play in learners' responsiveness to the adaptive assistance was explored.

5.2 Sample

5.2.1 Participants' profile

Participants (aged 18 or over) 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 lasting for at least four weeks, were randomised into one of two experimental conditions. Due to the nature of online courses, where learners on a single course may represent a number of different countries, this study aimed to recruit participants internationally.

5.2.2 Recruitment

The recruitment process included a variety of approaches. First, the virtual assistant was listed in the Chrome and Firefox web stores, alongside a description and screenshots of the tool. Second, participants were invited to participate in the study using social media, and a description of the assistant was posted on Facebook groups relevant to popular massive open online courses and course platforms. Third, an invitation to participate in the study was provided to participants of two MOOCs offered on coursera.org by Tomsk State University ('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 the courses' participants. 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. Finally, a website dedicated to the tool was published, consisting of a promo page with relevant information regarding the tool, which was indexed by search engines, generating additional traffic. During the data collection period 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 (the top 10 countries, calculated by the number of unique visitors to the project website).

5.2.3 Recruitment results

The flow diagram presented in Figure 5.2 illustrates the progression of participants 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 questionnaires. 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, post-intervention and follow-up are used interchangeably).

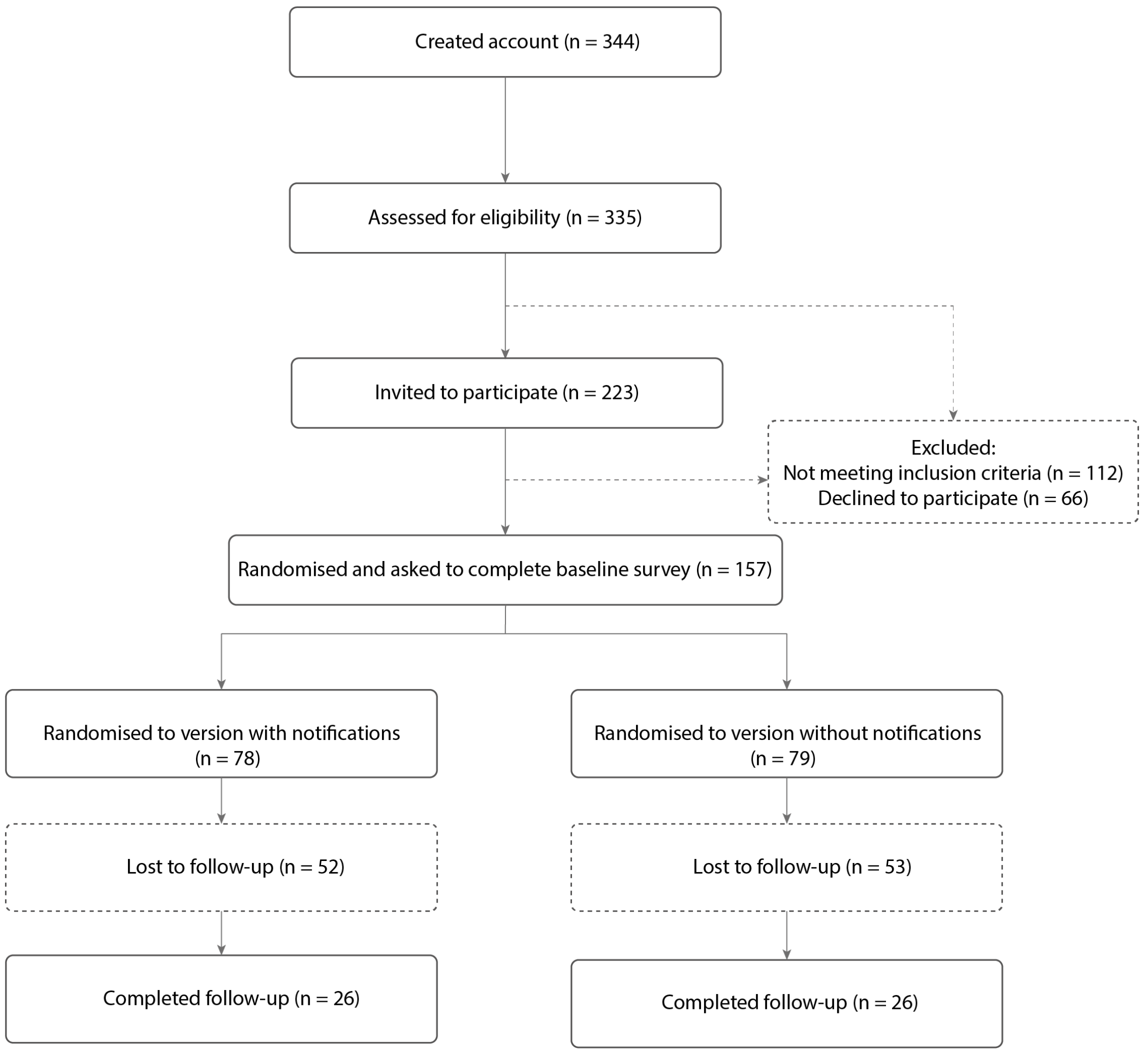


Figure 5.2 Flow diagram of participants' progress through the key phases of the study.

Participants (N=157) were predominantly male learners (70%) below 30 years old (M = 26.68, SD = 7.36). On average, participants 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). 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. Although this was an unexpected result, it supports existing research showing that using tracking devices and a voluntary post-intervention questionnaire leads to high attrition rate. The observed low response rate is consistent with previously reported high participants' attrition rate in educational and medical studies using tracking devices or a voluntary post-intervention questionnaire in studies focusing on MOOCs (see, for example, Kramer et al., 2019; and Jansen, van Leeuwen, Janssen, Conijn and Kester, 2020).

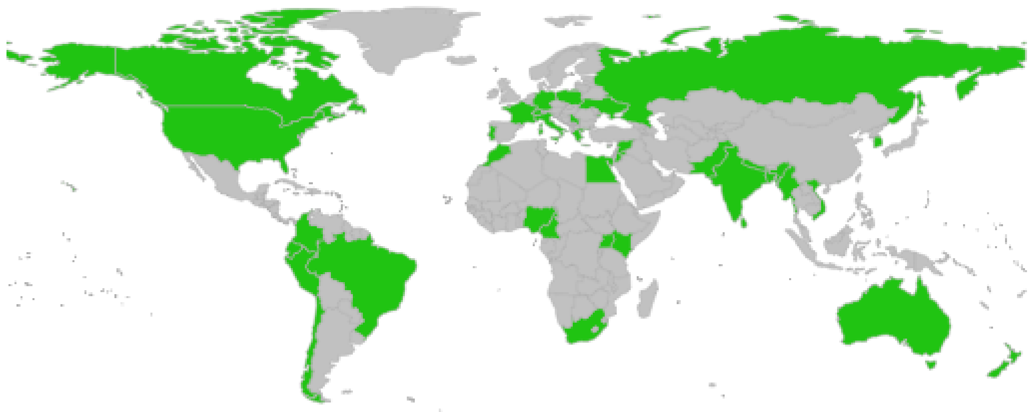


Figure 5.3 Map with countries indicated by participants.

There were 39 unique countries indicated by 145 participants (shown on the map in Figure 5.3). As the map shows, participants who took part in the study, and were willing to utilise the assistant, are distributed across continents, located in countries with varying levels of economic development.

To extrapolate findings from the present study to apply to the general MOOC learning population, it is important to verify that participants' demographic characteristics, such as age, gender, level of received education, and online learning experience, as presented in Table 6.1 on page 105, are associated with the general population of MOOC learners. It has been shown that MOOCs tend to be dominated by male learners; the usual ratio is 2:1 in favour of male participants (Glass, Shiokawa-Baklan and Saltarelli, 2016, p. 43). However, these numbers vary according to course subjects, and, to some extent, by course platforms and participants' geographical distribution. 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 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 this study, as the table shows, the proportion of participants who indicated their gender as 'female' was 13.4%. However, a relatively high proportion of participants did not provide their gender (14.6%); it is unclear if female learners prefer not to report their gender. MOOC participants' median age is usually described as below 30, but there has been an increasing tendency for participants aged 30 and older to take on these courses (Glass et al., 2016, p. 42). As the field of online learning matures, the age range of participants is widening as some school students and established professionals have started to more actively participate in MOOC learning. For example, MOOC learners' level of education has hitherto been dominated by participants with college degrees (Glass et al., 2016, p. 44), but the number of participants with a secondary school level of education has begun to increase, as reported by courses on the Futurelearn MOOC platform (Liyanagunawardena, Lundqvist and Williams, 2015, p. 561). As MOOCs become a widely accepted form of delivering educational programs and as options for students' self-study, more people have started to enrol in MOOCs, resulting in more participants with prior experience using MOOCs in more recent descriptions of MOOC participants' demographics. 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). Overall, it can be concluded that the sample for the present study mirrors the general MOOC learners' population in terms of age, gender, educational level, online learning experience, and learners' geographical distribution. A further exploration regarding participants' profiles of those who responded to the questionnaires is provided in the Results section (Chapter 6).

5.3 Intervention

The intervention tool (i.e. the virtual assistant), was implemented in the form of an application comprised of extensions to the Chrome and Firefox web browsers, a web interface with learning analytics and instruments to adjust personal settings, and a database with collected trace data. A detailed description of the tool and its components is outlined in Section 4.5. The choice of considering the above mentioned web browsers was determined by their popularity: nearly 80% of all internet desktop users use either Chrome or Firefox as their web browser (Netmarketshare, 2019).

The assistant provided a constant intervention component and an adaptive intervention component with a variety of individualised pop-up notifications. The constant intervention component included modules which aimed to support stages of self-regulated learning, including planning and goal setting, self-monitoring, and self-evaluation. This component included the following modules: (1) goal settings module, used to indicate an online course a participant intends to complete, alongside the required time-frame; (2) module with personalised settings to adjust a learner's web browser environment; (3) dashboards with learning analytics, illustrating the time spent online using different web resources; (4) dashboards with learning analytics illustrating time spent toward indicated goals.

The adaptive assistance intervention component evaluated in this study consisted of a variety of pre-designed message templates tailored to each participant. The time of the delivery of the intervention was based on a number of pre-specified decision rules based on learners' settings and their performed actions. The content of these templates was coded in accordance with the Behaviour

Change Technique taxonomy (Michie et al., 2011); their implementation as components of the intervention was guided by the Behaviour Change Wheel framework (Michie et al., 2014). The most relevant BCTs were selected based on developmental activities and compensatory strategies (see Chapter 4 for more details), with the final aim of supporting learners' self-regulated learning in mind. This resulted in 74 message templates which aimed to appear in the event of a failure of self-regulatory behaviour. These messages had 31 corresponding distinct BCTs, including: Feedback on behaviour; Information about social and environmental consequences; Information about emotional consequence; Problem solving; Action planning; Reward (outcome); Goal setting (behaviour); Goal setting (outcome); Reviewing behavioural goals; Discrepancy between current behaviour and goal; Review outcome goal; Behaviour contract; Commitment; Monitoring of behaviour by others without feedback; Self-monitoring of behaviour; Self-monitoring outcomes of behaviour; Monitoring behavioural outcomes without feedback; Feedback on outcomes of behaviour; Social support (unspecified); Social support (emotional); Instruction on how to perform behaviour; Information about antecedents; Re-attribution; Behavioural experiments; Information about consequences; Monitoring emotional consequences; Anticipated regret; Social comparison; Information about others' approval; Incentive (outcome); Body changes.

The content of the pop-up messages implemented in the adaptive assistance component was determined by (1) considered models of SRL (provided introduced in Section 2.3) with a particular focus on categories encapsulating self-regulatory strategies proposed by Zimmerman and Martinez-Pons (1986) (described in Section 3.1.1); (2) the examination of previously published results regarding research on the effectiveness of interventions to support learners' self-regulation (provided in Section 4.1 and Section 4.2); (3) the selection of BCTs, which provided additional intervention options (as described in Section 4.3). The expectation was to help learners to not simply compensate for a lack of self-regulatory skills by just change modifying their immediate actions and to compensate for a lack of self-regulatory skills, but to provide them with more long-term effects impulses in terms of self-regulatory skill development (in the form of scaffolding). Two examples of these pop-up messages are provided below. The first example is a message template with the next text *'If you feel tired, it might be more beneficial to spend time going for a walk rather than reading the news or checking your email. You could also try opening a study webpage in advance to resume your study session later'*. This message template can be attributed to the 'environment re-structuring' category of self-regulatory strategies, proposed by Zimmerman and Martinez-Pons (1986), and the 'Instruction on how to perform behaviour' BCT (according to the taxonomy of BCTs, provided in Michie et al., 2013). Another example is the message *'Do you believe that your studying tendencies are not helping you to achieve your set goals? Then try increasing your learning activity or review your study goals'*. This message can be considered as relevant to the 'self-evaluation' strategy (Zimmerman and Martinez-Pons, 1986), but also can be attributed to the fourth stage 'evaluation of progress and goal adjustment' of Winne's (Butler and Winne, 1995; Winne, 1996) SRL model (as described in Section 2.3.2). In addition, this message template was coded according to the 'Discrepancy between current behaviour and goal' BCT.

The main function of each message template was specified according to its relevant BCT. The functions related to Coercion (5 message templates), Education (4), Enablement (1), Environmental restructuring (3), Incentivisation (11), Modelling (4), Persuasion (12), and Training (34). Although it is possible to allocate more than one function to BCT message templates, to reduce the complexity of subsequent explorations, only one dominant function was indicated for each message template. In addition, 10 encouraging message templates were added to the list of templates, with the aim to enhance learning performance and to even extend a current learning session. These templates were triggered by different decision rules, appearing on learners' screens each time a participant spent 25 minutes on a course URL (as indicated by learners in their settings). For example, the following message was included in the list of encouraging templates: 'Your studying progress is impressive! Keep learning!'.

5.4 Design

As the main aim of this study was to evaluate the presence of developmental and compensatory effects of adaptive assistance on learners' self-regulation, a study that incorporates a combination of behavioural and self-report measures carried out, whereby enrolled study participants were randomised into control and intervention groups. To add an additional layer of support when attempting to detect potential short-term compensatory effects of the intervention, a micro-randomised trial for study participants in the intervention group was conducted in parallel. The schematic representation of this process is provided in Figure 5.4, which extends the previously illustrated Figure 4.9 on page 86 with the addition of the micro-randomisation functionality (highlighted by the red box).

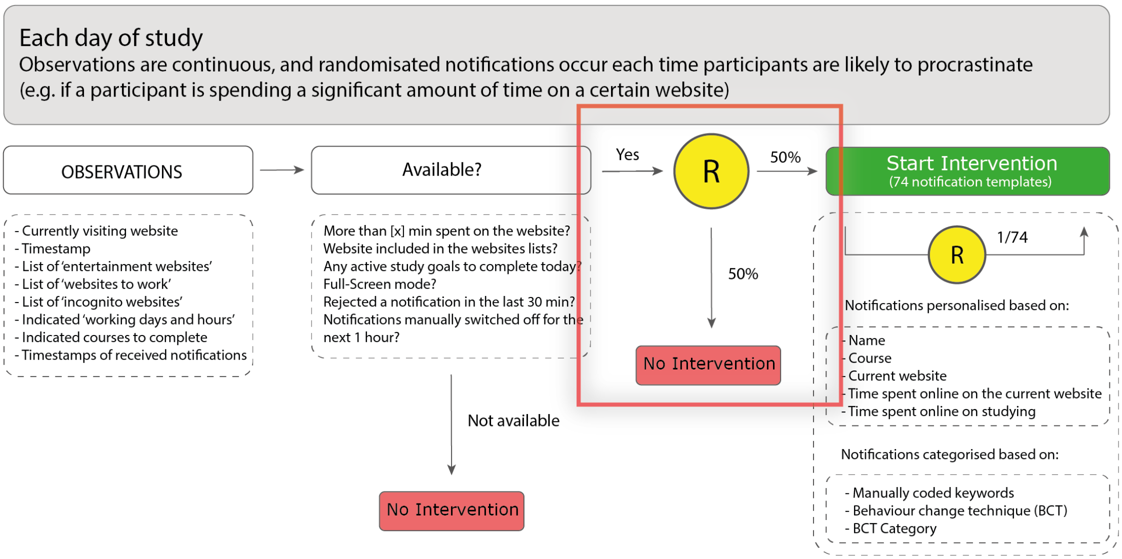


Figure 5.4 Schematic illustration of the adaptive assistance algorithm implemented within the intervention group micro-randomisation component.

During the study, each participant received a constant intervention component, while participants in the intervention group also received the assistance intervention component. This included personalised notifications which were sent at a probability of 50% at each decision point (pre-specified rules to indicate a decision point and a participant's availability for a prompt are given in the Figure 5.4). This design allowed the effect of these notifications to be evaluated as a package (with the frequency of 1/2 or 50%), and for the proximal effect of each notification to be considered. The former aims to evaluate the effectiveness of the intervention component, while insights from the latter can be utilised to explore the short-term effect of individual components that can be used then to inform design of an optimised and more efficient version of the adaptive assistance intervention. The rationale for providing participants in the control group with a constant intervention component helps to prevent excessive dropout from 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.

5.5 Measures

Baseline and self-report measures. Prior to using the virtual assistant, participants were asked to provide responses to questionnaires in order to ascertain baseline measures. To establish baseline measures, participants' demographic characteristics (age, gender, geographical location by country, educational attainment and prior online learning experience) were collected using a self-report questionnaire. Levels of self-regulation were assessed by administering the 24 item Online Self-Regulated Learning Questionnaire (Barnard, Lan, To, Paton and Lai, 2009). This questionnaire is comprised of 24 questions (Appendix A) covering 6 sub-dimensions of self-regulated learning with a 5-point Likert-type response format, ranging from 'Strongly disagree' (1) to 'Strongly agree' (5). Higher scale scores are expected to be indicative of better self-regulatory skills. For the present study, participants' responses to each subscale were averaged to obtain a respective scale score. The mean score across these six scale scores represents the SRL total score. This questionnaire was developed with the intention to meet the demand for a valid and reliable instrument to measure learners' self-regulation in online and blended learning environments (Barnard et al., 2009). The 24 items in this questionnaire represent a selection from the item pool of 86 items in the original version, which was developed as a multi-dimensional instrument to measure self-regulated learning proposed by Zimmerman (1998) (see also Barnard-Brak, Paton and Lan, 2010a, p. 65). The short 24 item version of the questionnaire has been widely used in research examining online and blended learning environments (see, for example, recent studies employing this questionnaire: Li, 2019; Li, Baker and Warschauer, 2020; Papamitsiou and Economides, 2019; Vanslambrouck et al., 2019). This questionnaire demonstrated adequate internal consistency of scores with α = .90 (scores by subscale ranged from .85 to .92), as reported by Barnard-Brak, Paton and Lan (2010b). The test-retest reliabilities for each subscale reported by Barnard-Brak et al. (2010a) are generally of a psychometrically acceptable level between .76 and .90 (Pearson's r correlations for two surveys). In addition, this questionnaire has been translated, validated, and applied in different languages, for example, in studies with 45 Russian (Martinez-Lopez, Yot, Tuovila and Perera-Rodríguez, 2017) and 786 Chinese students (Fung, Yuen and Yuen, 2018).

As a marker of non-cognitive individual differences in participants' personality traits, the 20 item International Personality Item Pool questionnaire (Donnellan, Oswald, Baird and Lucas, 2006) with a 5-point Likert-type response format was administered. This questionnaire was constructed as a shortened version of the 50 item personality trait questionnaire (Goldberg, 1999) and comprises 20 questions (Appendix B). The 50 item questionnaire was based on over 2,000 items from the International Personality Item Pool (IPIP). This set of items was extensively examined and translated across dozens of languages (Goldberg et al., 2006) and, as a result, has become a well-known and frequently used instrument to measure personality traits (see, for example, meta-analyses of intercorrelations, validity and reliability, conducted by Hamby, Taylor, Snowden and Peterson, 2016; Trapmann, Hell, Hirn and Schuler, 2007; van der Linden, te Nijenhuis and Bakker, 2010). The initial evidence regarding the reliability and predictive utility of the 50 item personality trait questionnaire was provided based on responses from 501 adults (for more details regarding reliability, see Goldberg, 1999, pp. 12-16), and later confirmed in numerous studies. For example, the five-factor structure of this questionnaire was demonstrated across different gender and ethnic groups (Ehrhart, Roesch, Ehrhart and Kilian, 2008).

The 20 item mini-IPIP scale (as called by the authors) was chosen because longer questionnaires administered online tend to receive lower response rates (Galesic and Bosnjak, 2009). Based on a large sample of young adults (N = 15,701), this 20 item questionnaire was proven to be a valid and reliable instrument to measure personality traits; it exhibited a 5-factor structure, acceptable reliability, and criterion validity (Baldasaro, Shanahan and Bauer, 2013). In addition, the questionnaire was translated into various languages and tested on various populations. For example, the Portuguese version of the questionnaire based on 2,153 participants demonstrated acceptable psychometric properties of the questionnaire, in terms of the factor structure, internal consistency, and convergent validity (Oliveira, 2019). A confirmatory factor analysis of the French version of this questionnaire based on 1,308 participants' responses demonstrated adequate reliability and a delineated five-factor structure (Laverdière, Gamache, Morin and Diguer, 2020). In addition to healthy adult populations, this 20 item mini-IPIP scale demonstrated appropriate psychometric proprieties on adult patients with cancer, similar to previously validated studies conducted in the general population, as noted by Perry, Hoerger, Molix and Duberstein (2020).

Behavioural measures. The behavioural measures were built on collected trace data, comprised of a list of domains visited by each participant, e.g. 'facebook.com', 'instagram.com', 'durham.ac.uk' (without detailing the full URL), a timestamp of the visit and time spent on each domain. Data regarding participants' responses to notifications (e.g., in the form of on-screen pop-up messages) was also collected. This data included information regarding the acceptance or rejection of a pop-up message (e.g. clicks on 'do useful' or 'not now' buttons), the date and time of the receipt of a message, the name of the behaviour change technique associated with a given message, and keywords associated with a message. A proportion of time spent on educational web resources following a decision point associated with each message was calculated and included in the dataset. 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 enables further personalisation of the adaptive assistance.

Outcome measures. The outcome measures included primary and secondary outcomes. A change in scores when responding to the self-regulated learning questionnaire was considered to be a primary outcome (developmental changes), together with the ratio between time spent on learning-related web resources and the total time spent online (compensatory changes). Secondary outcome measures included indicators reflecting observed behaviour, such as changes in time spent on other categories of web resources (e.g. entertainment and social media), time spent on web resources categorised as educational and total time spent online following a decision point (indicating the need to provide an intervention) to access short-term and time-varying effects of the adaptive assistance.

5.6 Procedure

The data collection process operated as follows. A web link with an offer to create an account and install the assistant browser extension was posted online or sent to learners who had registered for an online course. Learners and internet users who were curious and willing to use this tool clicked on the link included in the email or posted online. They were then transferred to the assistant website, where visitors were able to create an account and install the extension to their web browser. During the registration process, learners were assessed according to the inclusion criteria, and learners who met the eligibility criteria were informed of the study. Those learners who expressed an interest in participating in the study were asked to accept the declaration of informed consent prior to data collection.

At this step, the participants (learners who satisfied the inclusion criteria and provided informed consent) were randomised into one of two conditions: the 'control' and 'intervention' group. These two conditions were distinguished by the presence of adaptive online learning assistance in the form of personalised in-browser notifications for participants in the intervention group. Following the registration process, participants were offered to complete questionnaires regarding their demographic characteristics, their level of self-regulated learning, and personality traits. The application then began collecting trace data relating to each participant's activity. Users who did not meet the inclusion criteria or refused to provide informed consent were not included in the study, but were given access to the version of the tool with adaptive assistance in their browser environment.

The total duration of the study for each participant consisted of 30 days. No reward or remuneration for participants was provided. Behavioural trace data were collected during a four-week period. 30 days after each participant's enrolment, the Online Self-Regulated Learning Questionnaire was re-administered to each participant. All collected data were anonymised and used solely for research purposes.

5.7 Data analysis

Prior to answering the main research questions, an initial analysis of participants' baseline characteristics and attrition was conducted. This analysis included a series of t-tests and the application of decision tree algorithms, performed to examine differences between participants' sub-samples. Conducted t-tests were supplemented by their 95% confidence intervals and effect sizes. Several factors determined this choice. First, the t-test is a robust and straightforward approach for hypothesis testing, allowing the examination of the presence of any differences between groups (Brooks, 2003, p. 2694). Second, calculated 95% confidence intervals provide additional assurance in the case of the presence or absence of any differences between groups (for more details regarding confidence intervals, see Cumming and Finch, 2005, p. 171). Third, reporting effect sizes facilitates the comparability of results across analyses involving different sub-sample sizes. Therefore, effect sizes are considered the most informative outcome of empirical studies (Lakens, 2013, p. 1). Furthermore, Hedges' g was chosen to calculate effect sizes as this method allows bias to be corrected, preventing the overestimation of the true population effect (Lakens, 2013).

In the primary analysis, the effect of adaptive assistance on developing and compensating self-regulation among online learners was evaluated by comparing outcomes obtained from the intervention and control groups. Repeated measures tests and random effect modelling were carried out to assess the effect of the adaptive assistance component on the self-report measures. To assess the compensatory effect of the adaptive assistance on main outcomes, polynomial regression curves were fitted to examine trends in observed behaviour. A combination of the mentioned approaches was utilised to ascertain the role of individual differences in compensatory and developmental shifts in the self-regulation of learning. Due to the complex data structure of collected behaviour traces and the fact that the procedure applied to analyse these traces was not pre-specified, a detailed description of the data analysis is provided in the Results section (Chapter 6) alongside the findings received. This approach allows the rationale and a detailed description of the chosen data analyses techniques to be provided together, with the results presented coherently and logically. Furthermore, it should be noted that the conducted data analysis was not pre-specified, and the risk of an unintentional reporting bias may exist as the consequence of it (Dwan et al., 2008; Schulz, Altman and Moher, 2010).

6 Results

6.1 Baseline characteristics and participants' attrition

An overview of the participants' characteristics, extracted from the pre-intervention (baseline) questionnaire, is presented in Table 6.1 on page 105. This table provides an overview of participants' self-report individual differences before their exposure to the intervention, and it provides the basis for examining the results of the randomised allocation of participants to different experimental conditions. A brief look at this table shows, reassuringly, that there were no any apparent differences between participants allocated to the two experimental conditions, with variations in terms of age, gender, level of education, and personality traits[1].

The summary of (self-reported) individual differences at baseline provided in Table 6.1 also illustrates the difference in participants' willingness to respond to the post-intervention questionnaire. For instance, participants whose scores were initially high (when compared to other participants) in openness to experience were more likely to answer the post-intervention questionnaire. Participants' online learning experience was also noticeably different in those who responded to the post-intervention questionnaire. This could be due to participants' dropping out of their online courses and discontinuing use of the assistant, as participants with little or no prior experience in online learning on massive online courses are more likely to drop out from their courses (Greene, Oswald and Pomerantz, 2015, pp. 944-945).

[1]All responses provided by participants regarding their demographic characteristics are presented in the table. As there was a limited number of responses in extreme values, responses have been aggregated into broader categories (e.g. postgraduate level of education and higher; participants with and without online learning experience), which allows the assumption that there is no apparent difference between groups.

Table 6.1 Description of participants' individual differences at baseline.

	All participants			Participants responded to follow-up		
	Overall	Control	Intervention	Overall	Control	Intervention
N	157	79	78	52	26	26
Age (mean (*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 (mean (*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)
Baseline SRL (mean (*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)

The difference in the overall level of (self-reported) self-regulation between participants who responded to the follow-up questionnaire and all enrolled participants indicates that participants with perceived high 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 and Hwang, 2016; Lin, Lai, Lai and Chang, 2016; Martinez-Lopez et al., 2017) the average level of participants' SRL scores assessed by utilising the Online Self-Regulated Learning Questionnaire with a 5-point Likert-type response format was 3.32, with a standard deviation of 0.9 across all four 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 appear to be significantly different to previously reported studies. To examine a particular subscale at baseline contributed to the difference in overall self-report self-regulation score and participants' willingness to provide follow-up (to complete post-intervention questionnaire), Table 6.2 was constructed.

Table 6.2 Description of participants' levels of self-regulation (including the overall level and subscales) at baseline.

	All participants			Participants responded to follow-up		
	Overall	Control	Intervention	Overall	Control	Intervention
N	157	79	78	52	26	26
Baseline SRL (mean (*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)
Subscales (mean (*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)
Env. 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)

It can be noted from Table 6.2 that there was no noticeable difference between baseline responses between the control and intervention groups among all participants. However, the participants allocated to the control group who responded to the post-intervention questionnaire had a distinctly different level of self-regulation in the task strategies subscale at baseline, compared with all enrolled participants. To test these assumptions and to examine whether there were any significant differences in participants' self-report personality traits at baseline, a more formal evaluation was performed. The results are presented in Table 6.3, and Table 6.4.

Table 6.3 Results of comparison analyses of responses from participants allocated to the control and intervention groups to the pre-intervention questionnaire (baseline measures).

	N	Mean diff.	t	p	95% CI	Hedges' g
Age	144	-0.86	-0.7	.49	[-3.28...1.57]	-0.12
Big Five						
Agreeableness	125	-0.2	-1.45	.15	[-0.46...0.07]	-0.26
Conscientiousness	125	0.07	0.54	.59	[-0.19...0.33]	0.1
Extraversion	125	-0.08	-0.67	.5	[-0.34...0.17]	-0.12
Neuroticism	125	-0.13	-1.19	.24	[-0.34...0.08]	-0.21
Openness	125	0.08	0.51	.61	[-0.23...0.39]	0.09
Overall SRL	137	-0.03	-0.17	.87	[-0.34...0.28]	-0.03
Goal setting	137	0	0.02	.98	[-0.35...0.36]	0
Env. structuring	137	0.1	0.57	.57	[-0.25...0.45]	0.1
Task strategies	137	-0.19	-1	.32	[-0.58...0.19]	-0.17
Time management	137	0.05	0.23	.82	[-0.37...0.46]	0.04
Self evaluation	137	-0.08	-0.45	.65	[-0.41...0.26]	-0.08
Help seeking	137	-0.03	-0.16	.88	[-0.44...0.38]	-0.03

A series of t-tests were performed in order to examine the difference at baseline between participants allocated to the control and the intervention groups. The results of the analyses performed, alongside their p-values, 95% confidence intervals, and calculated effect sizes (Hedges' g) are provided in Table 6.3. The findings from this table indicate that there were no significant differences between participants allocated to different experimental conditions. Therefore, it can be concluded that the randomised allocation was applied effectively, and that there was no systematic bias between the two groups at baseline, based on the pre-intervention participants' responses.

The results of the comparison analyses of participants who responded to the post-intervention questionnaire and those who did not provide responses are

Table 6.4 Results of comparison analyses of baseline measures between participants who completed and lost to the post-intervention questionnaire.

	N	Mean diff.	t	p	95% CI	Hedges' g
Age	49|95	1.32	0.92	.36	[-1.54...4.18]	0.18
Big Five						
Agreeableness	52|73	0.33*	2.46	.02	[0.06...0.6]	0.44
Conscientiousness	52|73	0.07	0.48	.63	[-0.2...0.33]	0.09
Extraversion	52|73	0.02	0.14	.89	[-0.25...0.29]	0.03
Neuroticism	52|73	0.08	0.64	.52	[-0.16...0.31]	0.13
Openness	52|73	0.55*	3.65	<.01	[0.25...0.86]	0.67
Overall SRL	52|85	-0.39*	-2.54	.01	[-0.69...-0.09]	-0.43
Goal setting	52|85	-0.15	-0.81	.42	[-0.51...0.21]	-0.14
Env. structuring	52|85	-0.21	-1.14	.26	[-0.57...0.15]	-0.2
Task strategies	52|85	-0.41*	-2.08	.04	[-0.8...-0.02]	-0.36
Time management	52|85	-0.55*	-2.58	.01	[-0.97...-0.13]	-0.46
Self evaluation	52|85	-0.4*	-2.42	.02	[-0.72...-0.07]	-0.41
Help seeking	52|85	-0.61*	-3.01	<.01	[-1.01...-0.21]	-0.52

*p < .05

presented in Table 6.4. These results indicate that participants who responded to the post-intervention measures had different scores in the overall level of self-regulation, particularly in four of the six subscales of the SRL questionnaire. Furthermore, respondents showed different results at their baseline levels of personality traits. As can be seen from the table, participants who scored lower on agreeableness and openness to experience personality traits were more likely not to respond to the post-intervention questionnaire. In terms of participants' responses to the SRL subscales, the results proved to be the opposite: participants with higher baseline scores in task strategies, time management, self evaluation, and help seeking subscales were less likely to complete the re-administered questionnaire. These results can be further explored by looking at the visualisation presented in Figure 6.1. The dots on this visualisation show participants' overall self-report scores in self-regulation. Some dots are connected by lines, which indicate individual changes in participants in cases where they provided both (pre- and post-intervention) responses.

As can be seen from the left panel of Figure 6.1, participants from the control

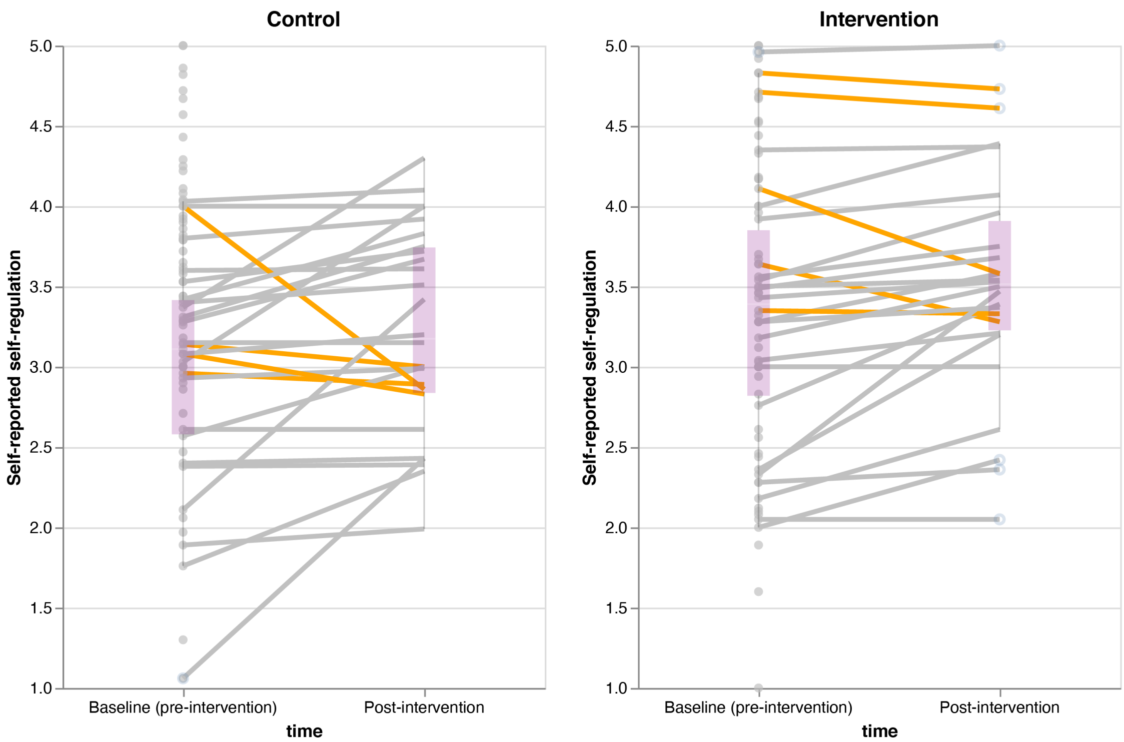


Figure 6.1 Change within individuals in response to the self-report questionnaire for each group.

group with initial high scores in self-regulation were more likely to not provide follow-up. The perceived lack of derived benefits in using the tool experienced by this cohort could be one possible explanation for this disproportion. This result can be explained by the assumption that learners with high initial scores in self-regulation are perhaps more likely to be aware of their weaknesses, and were in search of an instrument which would more actively support their learning. Furthermore, the decision to not adopt the tool can be considered the application of a self-regulatory strategy.

Additionally, Figure 6.1 shows that the distribution of baseline responses of all enrolled participants allocated to different experimental conditions is nearly equal. In both groups, there were participants with an initial overall score of SRL distributed across the full range. The variability of participants' post-intervention responses in the intervention group has less variation in comparison to the control group. It can be noted from the figure that some learners with extreme initial scores demonstrated outstanding changes in their self-report SRL at the post-intervention response. For example, participants with high baseline scores in overall self-regulation who were allocated to the intervention group showed negative trajectories (see the upper right section of the figure). Another notable example is that one participant assigned to the control group with a low overall baseline SRL score showed significant improvement in the post-intervention response to the questionnaire. Overall, it can be concluded that the differential effect in participants' willingness to respond to the post-intervention questionnaire depends on the interaction between personal characteristics and the situational factor of being exposed to the intervention.

In addition, among those participants who responded to the post-intervention measures, the collected baseline data were evaluated for any dissimilarities between participants' allocated to different experimental conditions. The results of a series of t-tests, analogously to the previous two tables, are provided in Table 6.5.

Table 6.5 Results of comparison analyses of baseline measures between participants who provided the follow-up, according to control and intervention groups.

	N	Mean diff.	t	p	95% CI	Hedges' g
Age	49	-0.67	-0.26	.8	[-5.92...4.58]	-0.07
Big Five						
Agreeableness	52	0	0	1	[-0.41...0.41]	0
Conscientiousness	52	-0.02	-0.09	.93	[-0.47...0.43]	-0.02
Extraversion	52	-0.3	-1.31	.2	[-0.76...0.16]	-0.36
Neuroticism	52	-0.14	-0.68	.5	[-0.57...0.28]	-0.19
Openness	52	0.33	1.37	.18	[-0.15...0.81]	0.37
Overall SRL	52	-0.36	-1.62	.11	[-0.8...0.09]	-0.44
Goal setting	52	-0.26	-0.92	.36	[-0.82...0.31]	-0.25
Env. structuring	52	-0.29	-1.02	.31	[-0.88...0.29]	-0.28
Task strategies	52	-0.81*	-2.8	.01	[-1.39...-0.23]	-0.76
Time management	52	-0.12	-0.34	.74	[-0.8...0.57]	-0.09
Self evaluation	52	-0.4	-1.68	.1	[-0.88...0.08]	-0.46
Help seeking	52	-0.26	-0.84	.41	[-0.87...0.36]	-0.23

*$p < .05$

The results of the comparison analyses between the baseline characteristics of participants who responded to follow-up showed that participants from both groups shared both age and personality traits at baseline. Only one statistically significant difference can be observed for scores in the participants' pre-intervention responses to the task strategies subscale of the SRL questionnaire. Although, the effect size of participants' differences in overall scores of SRL and the self evaluation subscale are close to medium, it cannot, however, be concluded that participants differ in terms of their overall scores (of baseline self-regulation) and the self evaluation subscale. As previously discussed, this difference could be explained by participants' exposure to the intervention. Participants with high baseline scores in the task strategies subscale who might be aware of their problems with procrastinatory behaviour might expect to receive additional support in the form of adaptive assistance. However, this form of support was only available for participants allocated to the intervention group. The lack of such support might, therefore, affect participants' willingness to respond to the post-intervention questionnaire.

Based on the comparison analyses conducted, taken together, it can be concluded that the randomisation was applied correctly, with no evidence of differences between all enrolled participants at the baseline between those allocated to the control and intervention groups. In terms of the participants who responded to the post-intervention questionnaire, a statistically significant difference was only observed for the task strategies subscale of the SRL questionnaire. However, there was no evidence of any difference in the overall level of SRL at baseline between groups. Due to the nature of the experiment, allocation to the control group and participants' exposure to the basic functionality of the tool resulted in a visible failure to complete the follow-up for participants with high baseline scores in self-regulation. One possible explanation is that participants with high baseline scores in self-regulatory skills were looking for an instrument to improve their skills further, and were likely to drop out after not receiving the full functionality of the tool. Further, differences in the baseline characteristics of participants who responded to the post-intervention questionnaire and those who did not provide a post-intervention response were also observed in the collected data.

The findings of the comparison analyses can be further explored by applying a decision tree algorithm to predict individual differences between participants who were likely to respond to the post-intervention questionnaire, based on available data. This algorithm was applied to the collected data relating to participants' individual differences, as presented in Table 6.4.

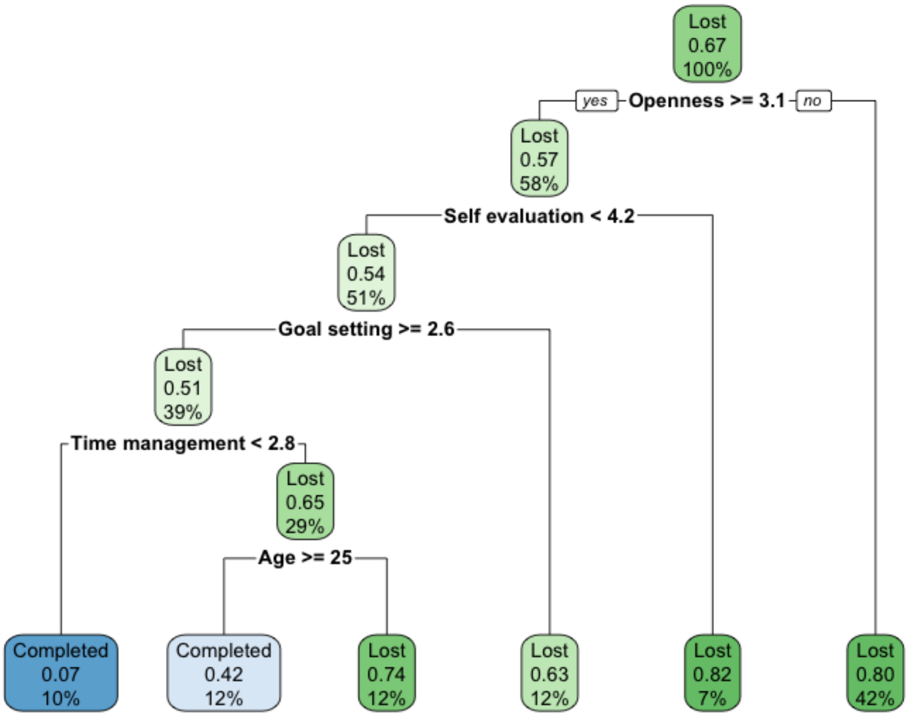
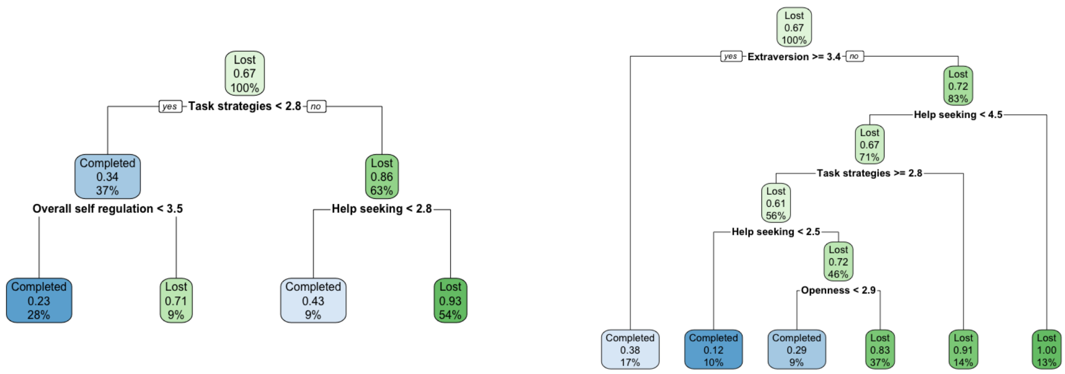


Figure 6.2 Decision tree of participants' attrition to follow-up.

The results of the decision tree algorithm application are illustrated in Figure 6.2. At the top of the figure, the overall probability of the participants' completing the post-intervention questionnaire is provided. It can be seen at the top node of the figure that the proportion of participants lost to follow-up is 67%, or 105 participants out of the 157 enrolled. The underlined nodes mark moments when participants' individual characteristics meet certain criteria. The first criterion filters all participants into two groups: participants who scored lower than 3.1 on a five-point Likert-type scale in openness to experience ('no' or the right direction line), and participants who scored higher or equal to 3.1. The right hand line leads to the root's right child node, which illustrates that 42% of participants scored lower than 3.1 in openness to experience and their probability to fail to provide a response to the post-intervention measure was 80%. On the left side, 58% of participants scored 3.1 or higher in openness, and only 57% of them were lost to follow-up. Further exploration of subordinate levels provides a clue regarding the role of individual differences in participants' loss to follow-up. In this figure, results are based on the best predictor available as the top-level node. If the 'openness to experience' personality trait was removed from the dataset, then 'agreeableness' would be used as the top-level node with a re-calculated sequence of subsequent nodes and their corresponding values. Similar trees can be constructed for each experimental group of participants.



(a) Decision tree of participants' attrition to the follow-up (control).

(b) Decision tree of participants' attrition to the follow-up (intervention).

Figure 6.3 Decision tree of participants' attrition to the follow-up by experimental condition.

The results for each experimental group are presented in Figure 6.3. It can be seen from the trees in this figure that predictors are different for each group. Without diving into their description, which can be seen in the figure, it is useful to note that individual differences, such as personality traits (e.g. openness to experience) and demographic characteristics illustrated in the previous figure (age), can provide particular practical implications for future studies. The results obtained after applying a decision tree algorithm to the available data can be utilised as predictors in estimating attrition rate. For instance, it allows participants' response rate to a post-intervention questionnaire to be estimated. An estimated response rate, in turn, can be used to determine the need for additional activities to facilitate enrolment to meet the requirement of a pre-calculated sample size, without the need to wait until the end of a data collection period. This is especially relevant to studies that are based on the use of a tracking device as a data collection tool (due to the previously mentioned issues surrounding the low response rate to the follow-up), or in research designs with strict time constraints, and where participants' retention is crucial. Finally, the results obtained in this study can be used when calculating the required sample size and power for a study with a similar design which, as here, takes into account the participants' attrition rate.

6.2 Development of self-regulation

This section aims to answer the first research question: whether the development of self-regulatory skills in learners can be facilitated by adaptive online learning assistance. To evaluate the developmental effect of adaptive assistance, based on the self-report SRL questionnaire, a between and within groups univariate repeated measures analysis was applied to each subscale. The application of the repeated measures procedure requires that the data considered meets certain criteria, including the independence of observations, the normal distribution of dependent variables, and the assumption of sphericity (i.e. equality of variances). Before examining differences in post-intervention responses to the SRL questionnaire between groups (main outcome), the collected data were examined in order to ascertain whether they met these assumptions. Outcome variables (post-intervention scores for six SRL subscales) used as dependent variables were continuous, and the factor of interest was represented as two groups of participants' allocation (control and intervention). As there were two events where responses to the SRL questionnaire were provided (pre- and post-intervention), the study formed a two-level data structure, and the assumption of sphericity was automatically met. The applied research design and randomisation of participants allows for the conclusion that these observations were indeed independent of each other. To review data for the presence of a normal distribution of dependent variables, Table 6.6 offering a summary of post-intervention responses to the SRL questionnaire, was constructed.

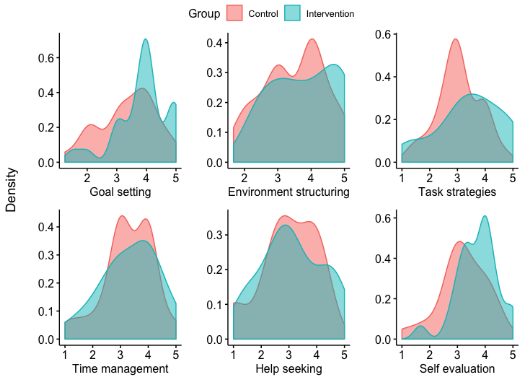
It can be concluded from the table that there are no large differences between means of outcome variables, their standard deviations or range values. Large negative kurtosis of the post-intervention measure of environment structuring (in the cases of both groups) and the help seeking subscale for participants in the intervention group indicate a platykurtic distribution shape (i.e. having a flattened peak, compared to the normal distribution curve). The noticeable negative

Table 6.6 Summary of post-intervention responses to the self-report questionnaire.

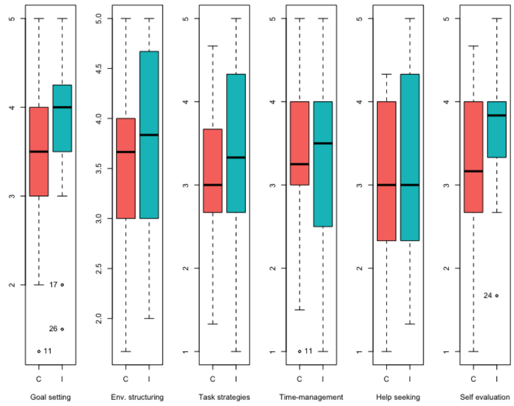
	Mean	*SD*	Median	Min	Max	Range	Skewness	Kurtosis	SE
Control group ($N = 26$):									
Goal setting	3.37	0.96	3.50	1.25	5.00	3.75	-0.37	-0.79	0.19
Env. structuring	3.47	0.95	3.67	1.67	5.00	3.33	-0.18	-1.09	0.19
Task strategies	3.05	0.78	3.00	1.33	4.67	3.34	-0.09	-0.39	0.15
Time management	3.29	0.91	3.25	1.00	5.00	4.00	-0.58	0.06	0.18
Help seeking	2.99	1.00	3.00	1.00	4.33	3.33	-0.56	-0.62	0.20
Self evaluation	3.21	0.84	3.17	1.00	4.67	3.67	-0.55	0.13	0.17
Intervention group ($N = 26$):									
Goal setting	3.87	0.87	4.00	1.50	5.00	3.50	-0.85	0.53	0.17
Env. structuring	3.78	0.99	3.84	2.00	5.00	3.00	-0.17	-1.42	0.19
Task strategies	3.42	1.16	3.33	1.00	5.00	4.00	-0.43	-0.74	0.23
Time management	3.33	1.03	3.50	1.00	5.00	4.00	-0.37	-0.63	0.20
Help seeking	3.12	1.11	3.00	1.33	5.00	3.67	0.02	-1.13	0.22
Self evaluation	3.72	0.73	3.84	1.67	5.00	3.33	-0.51	0.50	0.14

skewness for the post-intervention scores in goal settings subscale for the intervention group suggests that the distribution of this outcome is left-skewed (i.e. many participants in the intervention group responded with high scores in goal setting at post-intervention). Overall, skewness and kurtosis of the post-intervention measures seem to be in the range of acceptable limits, which suggests univariate normality of each variable. Skewness and kurtosis can be further evaluated by examining distributions of the post-intervention measures presented in a graphical form. The distribution of outcomes presented in the left panel of Figure 6.4 and differences in outcomes visualised as box-plots in the right panel of the figure support the conclusions regarding normality of the dependent variables.

The results of repeated measures analyses at pre- and post-intervention for the measures of SRL subscales are presented in Table 6.7. This table illustrates the results between and within-group change analyses, interaction effects between the time and group factors, their significance and effect size. The effect size was calculated using generalised eta squared (η^2_G). This approach to reporting effect



(a) Distribution of responses to the post-intervention SRL questionnaire.



(b) Box-plots of responses to the post-intervention SRL questionnaire.

Figure 6.4 Distribution and box-plots of responses to the subscales of the post-intervention SRL questionnaire.

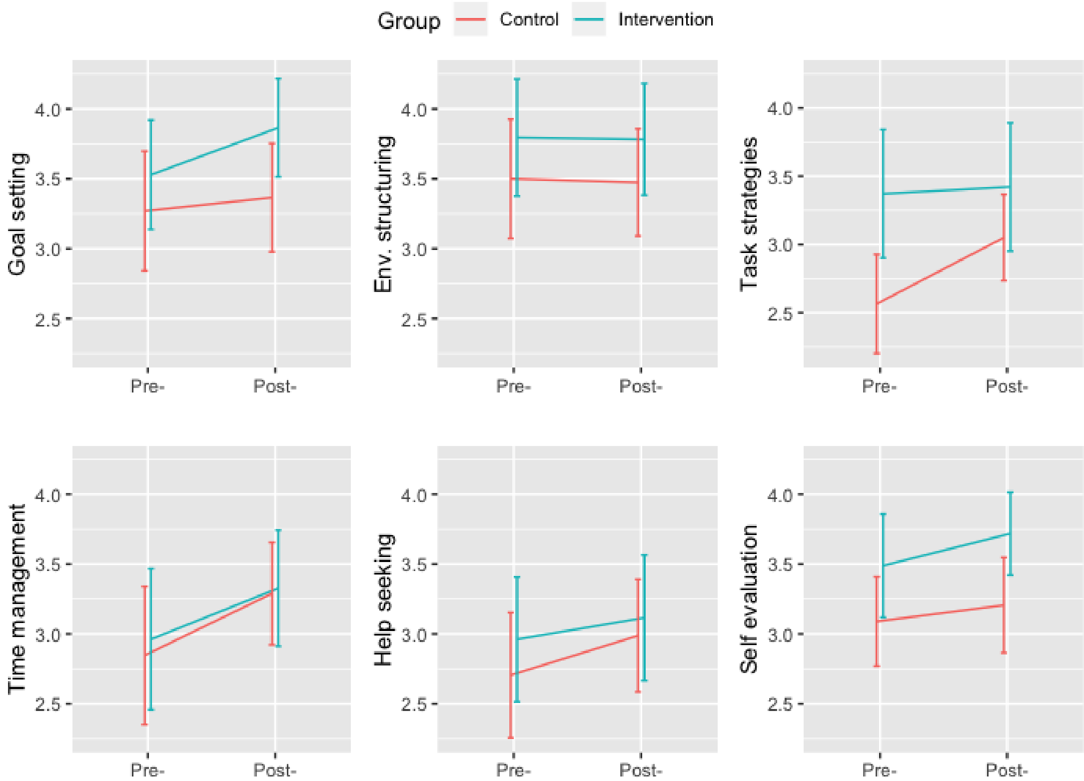


Figure 6.5 Graphical representation of changes within and between groups in self-report overall level of self-regulation in learning.

Table 6.7 Results of analyses using the repeated measures procedure at pre- and post-intervention for the measures of self-report self-regulation in learning.

	Pre-		Post-intervention				
Group	Mean	*SD*	Mean	*SD*	Effect	p	η^2_G
Goal setting							
Control	3.27	1.06	3.37	0.96	Time	.016	.013
Intervention	3.53	0.97	3.87	0.87	Group	.140	.039
					TxG	.174	<.01
Env. structuring							
Control	3.50	1.05	3.47	0.95	Time	.859	<.01
Intervention	3.79	1.04	3.78	0.99	Group	.247	.023
					TxG	.953	<.01
Task strategies							
Control	2.56	0.90	3.05	0.78	Time	<.01	.018
Intervention	3.37	1.16	3.42	1.16	Group	.034	.08
					TxG	<.01	.012
Time management							
Control	2.85	1.22	3.29	0.91	Time	<.01	.033
Intervention	2.96	1.25	3.33	1.03	Group	.787	<.01
					TxG	.752	<.01
Help seeking							
Control	2.70	1.11	2.99	1.00	Time	.033	.011
Intervention	2.96	1.10	3.12	1.11	Group	.5	<.01
					TxG	.522	<.01
Self evaluation							
Control	3.09	0.79	3.21	0.84	Time	.05	.011
Intervention	3.49	0.92	3.72	0.73	Group	.036	.074
					TxG	.511	<.01

size, in contrast to reporting eta squared or partial eta squared, allows comparability across studies that incorporate between-subject and within-subject designs (Bakeman, 2005, p. 383). In addition to between group effects, within groups changes were also reported, as participants allocated to the control group had access to the basic functionality of the tool. A similar approach to presenting change within and between groups has previously been applied in studies conducted by Titov et al. (2016) and Silfvernagel et al. (2018).

The results of the analyses presented in Table 6.7 suggest that participants allocated to the control group showed an improvement in the task strategies subscale of the SRL questionnaire, compared to participants assigned to the intervention group. However, as can be seen from the graphic representation of within and between group changes, as provided in Figure 6.5, the intervention group participants' scores for this subscale are higher at baseline, and their post-intervention response level for this subscale was nearly the same. There are also noticeably different slopes in goal setting and self evaluation subscales, however, it is statistically unclear if these changes were caused by providing the adaptive assistance intervention. Participants from both groups demonstrated nearly identical slopes in responses to the environmental structuring, time management, and help seeking subscales.

Repeated measures tests are a common approach to analysing educational interventions. Although no specific approaches reported in the literature on SRL research considered as the best option to evaluate SRL interventions (except that the frequency of different approaches to analysing data reported in systematic reviews of research on self-regulated learning can be calculated), a survey of the most suitable approaches to evaluate interventions was found in a neighbouring area of research — the effectiveness of digital game-based learning. Based on interviews with 13 experts in psychology and pedagogy, All, Nuñez Castellar and Van Looy (2016) reported that the majority of experts interviewed (10 out of 13) would suggest a standard repeated measure design for data analysis. However, two experts chose to utilise mixed effect models, taking fixed and random effects into account (All, Nuñez Castellar and Van Looy, 2016, p. 99).

As a form of sensitivity analysis, conducted to confirm results obtained with the repeated-measure tests, linear mixed effect models were fitted to each subscale with self-report measures as dependent variables, time and group as explanatory variables, alongside random intercepts for each individual. The application of linear mixed effect models allows for the reduction of hidden sampling bias, and the possibility of an inflated Type I error rate, as there was a limited number of participants in the final sample (i.e. participants who have also completed the post-intervention questionnaire). Fitting random intercepts for subjects allows for correlations between repeated measures, as suggested by Vehkalahti and Everitt (2019, p. 186). Fitting these models to each subscale provided the results in Figure 6.6, presented here in the form of a graphic representation of calculated coefficient estimates and their confidence intervals. This approach is an appropriate alternative to presenting results in a table format, as suggested by Cumming (2014), and has previously successfully applied to report findings elsewhere (see, for example, use of forest plots in Beckmann et al., 2020, Appendix C on page 18).

The forest plots in Figure 6.6 shows the ways in which the findings correspond to the results obtained using repeated-measure tests. Participants in the control group demonstrated an increase in the task strategies SRL subscale. It is also notable that, for participants allocated to the intervention group, the calculated coefficient estimates and their confidence intervals for both the goal-setting and self evaluation subscales differ from the rest of subscales. However, these results cannot be conclusively attributed to the developmental effect of the intervention, as the confidence intervals in both cases (goal-setting and self evaluation subscales) included the zero value, even in the case of considering 90% confidence intervals (displayed in the right corner of Figure 6.6). In conclusion, the results of this study indicate that the adaptive assistance provided by the virtual learning assistant did not result in noticeable developmental shifts in learners' self-regulation as assessed via conventional self-report measures.

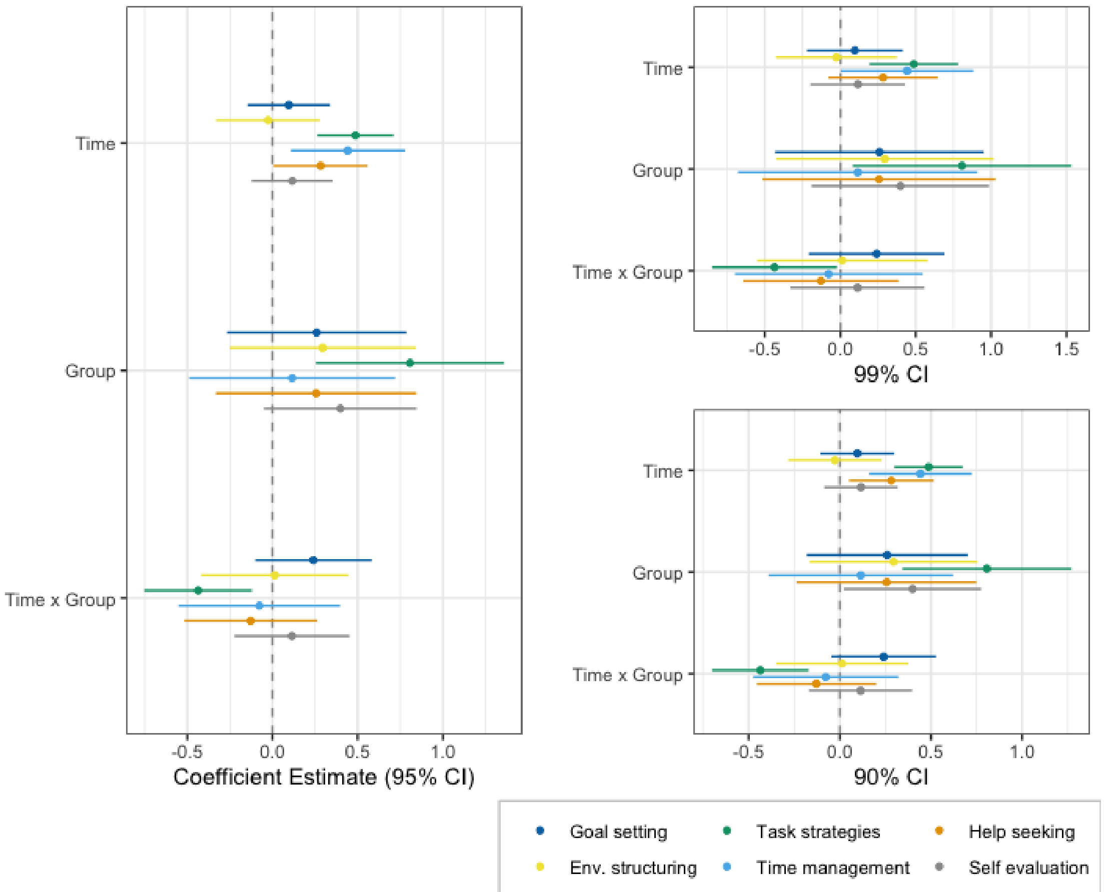


Figure 6.6 Coefficient estimates and confidence intervals of fitting linear mixed effect models with the explanatory variables ‘time’ and ‘group’, and random intercept for each individual.

6.3 Compensation of self-regulation

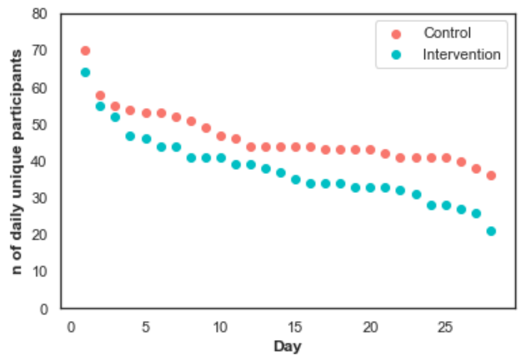
This section aims to answer the second research question: whether a lack of self-regulatory skills in learners can be compensated for by providing adaptive online learning assistance. To answer this research question regarding compensatory functions of the adaptive assistance intervention, collected behaviour data was examined. The collected dataset of participants' web navigation and interactions with their web browser environments (trace data) consisted of 443,131 records among 134 participants. An example of the collected data is presented in Table 6.8. This table presents a data subset, with a sequential web navigation. It can be noted from these data that between the first and second illustrated records, there was a period of inactivity lasting about one and a half minute (from 13:50:07 to 13:52:30 in the participant's local time), during which the participant performed activity outside their web browser. After returning to their web browser, the participant visited several web pages for a short period of time, an activity similar to switching between already opened tabs in a browser.

Table 6.8 Example of collected behaviour traces.

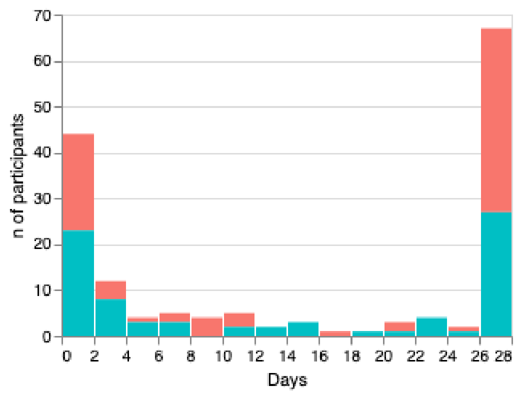
User Id	URL	Timestamp (local time)	Seconds on URL	Timestamp (UTC)
00021567	douseful.com	2019-07-21 13:50:48	19	2019-07-21 18:50:48
00021567	douseful.com	2019-07-21 13:52:30	2	2019-07-21 18:52:30
00021567	coursehero.com	2019-07-21 13:52:32	4	2019-07-21 18:52:32
00021567	chrome.google.com	2019-07-21 13:52:36	10	2019-07-21 18:52:36
00021567	docs.google.com	2019-07-21 13:52:46	5	2019-07-21 18:52:46
...				
443,131 rows				

In order to examine participants' behaviour trace data on aggregated level to examine differences between experimental groups, several data transformation steps were taken. As data collection was distributed across several months and participants enrolled in the study at different dates, it was necessary to standardise time series data for comparability between participants on the same time scale (i.e. days in the study). After standardising time-series data, participants' retention to use the virtual learning assistant was evaluated.

Participants' retention based on behaviour traces is illustrated in Figure 6.7. Behaviour trace data consists of data linked to 70 participants allocated to the control group, and 64 participants assigned to the intervention group. It can be noted from the Figure 6.7 (a) that the number of unique daily participants allocated to different experimental conditions have a similar dropout trend, with a slightly accelerated slope for participants' loss from the intervention group. As can be seen on Figure 6.7 (b), there was a high dropout at the starting point of using the tool. However, many of the participants who used the assistant for at least one day went on to have records across several days. It can be seen from the graph that nearly 70 participants used the tool on a daily basis (26 to 28 days with records), which means that they used their web-browsers almost every day, and their web navigation behaviour was recorded. Another important aspect to keep in mind is that for those participants who used their web browser only several days a week (e.g. five days a week), the number of unique days with records would be less than 28 (for example, four weeks multiplied by five days of activity each week resulting in 20 days with records).



(a) Number of unique daily participants.



(b) Total days in the study

Figure 6.7 Participants' engagement in the main study.

The web navigation behaviour trace data consists of 17,064 unique URL records. Some, however, represented similar online resources, such as 'google.com' and 'google.co.uk', whereby marginally different domain names and sites, were given unique records. To overcome this issue, and to allow comparison across participants in terms of visited URLs, unique URLs were grouped into six major categories. The categorisation of the URLs worked through several steps. The functionality of the data collection instrument allowed participants to classify websites into 'productivity' and 'entertainment' categories, as mentioned in Section 4.5. Participants were able to create unique lists of websites for each category, where, in the case that participants were allocated to the intervention group, adaptive assistance was disabled during time spent on a website indicated by a learner as 'productive', or was triggered with a higher intensity if a participant was spending time on an URL from their list of 'entertainment' websites.

First, the two sub-tables included in Table 6.9 provide information regarding URLs which were categorised by participants as 'productive' and 'entertainment'. 171 URLs were categorised by participants as related to 'productivity', overall, while 72 were marked as 'entertainment'. As can be seen from these two sub-tables, some participants ($N = 12$) categorised YouTube as 'productive', while others ($N = 14$) categorised it as 'entertainment' (participants were not able to classify one URL into different categories). Such inconsistencies can be explained by the fact that some participants might use YouTube as a learning resource (e.g. to watch course lectures) while, for others, it might be one of many possible online distractors (e.g. to watch entertaining videos). Participants' categorisation of URLs and their indicated online courses was a starting point to categorise the full scope of domains visited.

Table 6.9 Categorisation of URLs.

(a) Web domains indicated by participants as 'Productivity'.

URL	Frequency
courses.edx.org	25
coursera.org	16
youtube.com	12
udemy.com	9
github.com	6
stackoverflow.com	5
startupschool.org	4
mail.google.com	3
w3schools.com	2
khanacademy.org	2

(b) Web domains indicated by participants as 'Entertainment'.

URL	Frequency
facebook.com	31
youtube.com	14
reddit.com	3
twitter.com	2
linkedin.com	2
web.whatsapp.com	2
discordapp.com	1
netflix.com	1
latercera.com	1
amazon.com	1

(c) Example categorisation of the most frequently provided URLs (first ten).

URL	Frequency	Category
youtube.com	54,570	youtube
facebook.com	41,860	social media
google.com	35,116	productivity
mail.google.com	15,679	productivity
docs.google.com	11,947	productivity
courses.edx.org	6,106	education
web.whatsapp.com	5,931	social media
github.com	5,506	productivity
drive.google.com	5,379	productivity
discordapp.com	4,354	entertainment

The next step in the URL categorisation process was to count the frequency of domain names in the trace data. The first 10 of the most frequently recorded

URLs are presented in the third sub-table of Table 6.9. For example, YouTube was the most commonly appeared URL in the collected trace data. The next step was to label the most common URLs manually, and the URLs frequently indicated by participants, into major categories. An example of this categorisation is given in the last column of the sub-table. It should be noted that, because of the inconsistent categorisation of YouTube by participants, and given that it was the most frequently appeared domain name, YouTube was given its own separate category.

The total number of unique web domains in the dataset among all participants was 17,064. The total number of manually coded URLs was 273, which was only 1.6% of all unique URLs. However, this small percent of categorised URLs accounted for 65.8% of all records, due to the high frequency of the categorised URLs, resulting in 291,500 records being categorised from the total 443,131. This categorisation accounted for 78.2% of all participants' recorded time spent online. The conducted URL categorisation resulted in a data frame with all unique URLs categorised into six categories: 'youtube', 'social media', 'productivity', 'education', 'entertainment', and 'other'. In the category of educational URLs, websites indicated by participants as their online courses (e.g. edx.org, coursera.org, w3schools.com) were added alongside frequently used and manually discovered known URLs, which may be related to indicated courses, such as ide.cs50.io for the course 'CS50's Introduction to Computer Science' on the platform edx.org. 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 included in the category of educational URLs. It is important to note that the categorisation of URLs into a broad range of categories may lead to a simplified understanding of the behaviour observed. However, this trade-off is an important step, allowing individual's behaviour to be compared across the variety of web resources visited.

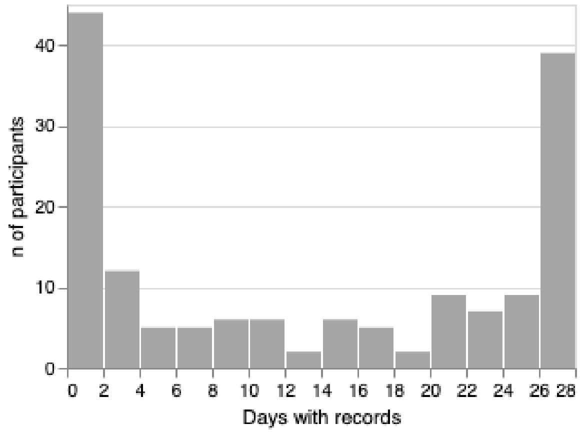
As mentioned, due to the participants' enrolment at different time points, to allow for comparison across a diverse range of recruitment dates, timestamps were standardised. The standardisation scale started from the date of the participants' registration at their local time (set as day 1) up to the next four week period, with the final date set as day 28. This step was performed in order to aggregate the

Table 6.10 Standardisation of days with web activity across participants.

(a) Examples of participants' standardisation of days scale for social websites.

	UserId	DateDayLocal	Day	Minutes
498	2e0fc105	2019-10-01	1	124.38
499	2e0fc105	2019-10-02	2	60.43
500	2e0fc105	2019-10-03	3	0.00
501	2e0fc105	2019-10-04	4	8.68
502	2e0fc105	2019-10-05	5	0.00
503	2e0fc105	2019-10-06	6	0.00
504	2e0fc105	2019-10-07	7	0.00
505	2e0fc105	2019-10-08	8	0.00
506	2e0fc105	2019-10-09	9	3.40
507	2e0fc105	2019-10-10	10	42.20

(b) Days with records for each participant (total for all categories).



total time each participant spent online. The same procedure was repeated for a subset of trace data representing each category of URLs. This manipulation resulted in a data file with an aggregated duration of time spent on each category by each participant, and for each day of the study. A subset of the resulting dataset is provided as an example in the left panel of Table 6.10. This subset consists of participants' time spent on URLs categorised as social media websites with participants' local time standardised as days since enrolment. The table demonstrates that this particular learner (represented in the subset) did not visit social media websites on certain days. Therefore, the dataset consists of zeroes in the column 'Minutes'. Analogously, these absences were apparent in the patterns of other learners and among other categories of websites. The resulting data representation is important, particularly, for educational websites, as while zero values (absence of time on educational URLs during a particular day) may have limited some visualisation options for continuous data, it allows hidden patterns to be extracted. For example, it provided the opportunity to observe the regularity of days with learning sessions.

As a result of the steps described above, participants' time spent on different categories of URLs was visualised in Figure 6.8 on page 126. In this figure, the time each learner spent online on different categories of websites is shaded in grey. The

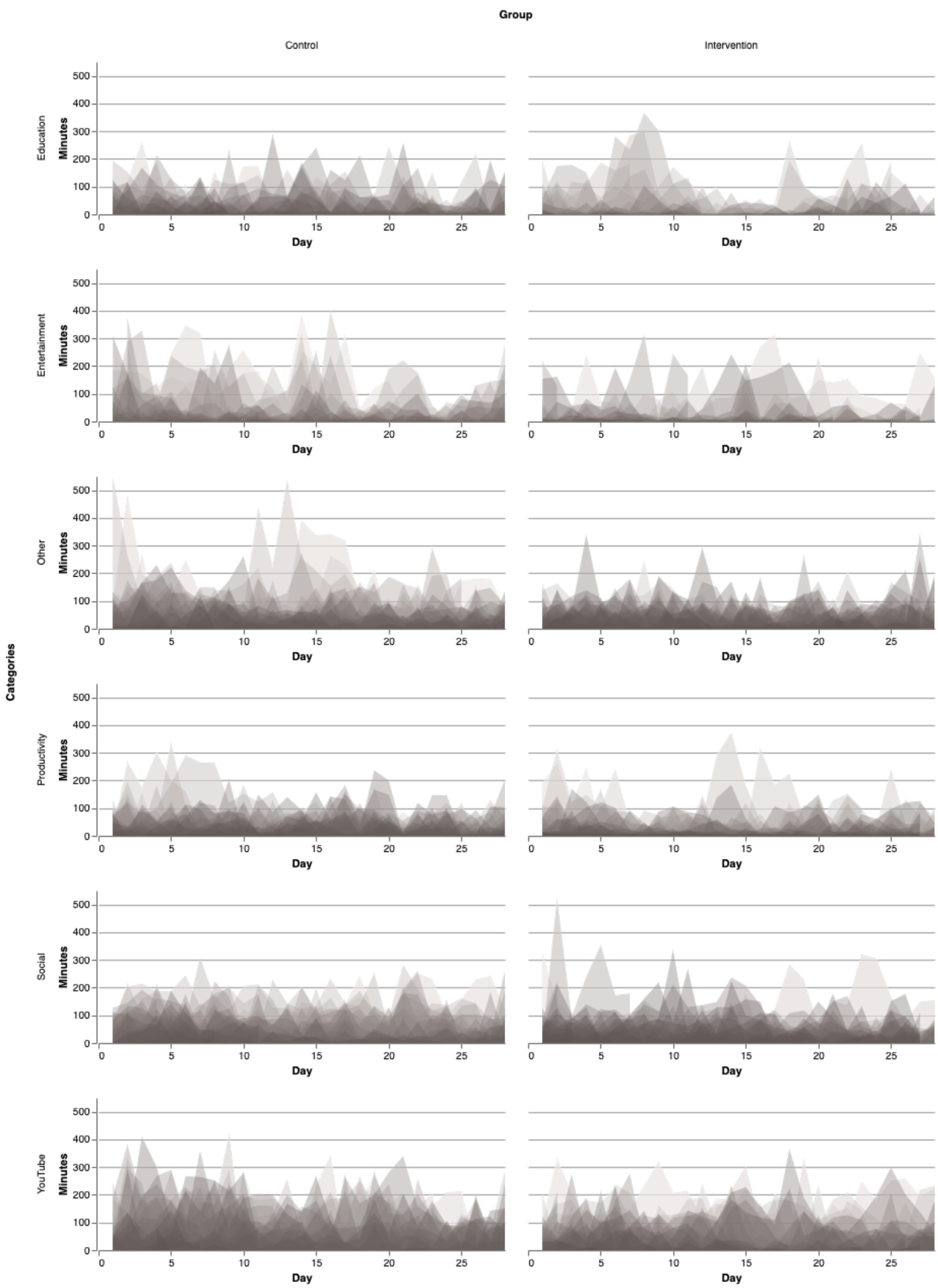


Figure 6.8 Time spent by individual participants on domain categories between groups (time in minutes).

dark concentration at the bottom of each graph suggests a high frequency of records surrounding low values. Light peaks represent individual learners' records for those days. It is noticeable from the first row of the graph, which refers to educational websites, that participants allocated to the intervention group showed a peak of time spent on educational URLs at the beginning and at the end of their enrolment in the study, with a noticeable decrease between day 13 and day 20 (although two peaks symbolise two participants' sessions on educational URLs near day 17). It is also noticeable that peaks in the first two weeks are not single outliers, but represent at least several participants (distinguished by grey tones).

Behaviour traces in terms of time spent on URLs categorised as entertainment can be described as having less variability for participants allocated to the intervention group, while participants from the control group showed some extremes in daily session lengths. The same description can be applied to the websites which were not labelled manually, and were listed in the 'other' category. There are discernible peaks in daily time given to social media websites for participants from the intervention group. Participants from the control group, meanwhile, spent time on social media uniformly across the 28 days. Time spent on YouTube across both groups presents some interesting patterns. The control group contributed more time at the beginning of the study, while participants from the intervention group caught up their counterparts on YouTube by the third week of the intervention. Participants' time spent on websites categorised as 'productivity' was distributed nearly equally across days. Thus, behaviour traces for participants allocated to the different experimental condition are distinguishable at the first look; further examination of traces could provide more details.

To further examine learners' time commitment to educational web resources, Figure 6.9 was constructed. The dots on this figure represent individual learners' time spent on educational URLs for a corresponding day (indicated on the x-scale). Lines on this figure describe the same data and, ideally, should connect all dots relating to a particular learner, in cases where there are no days with zero minutes on educational websites. As can be seen, participants allocated to the intervention group had more lengthy web sessions on educational URLs from days

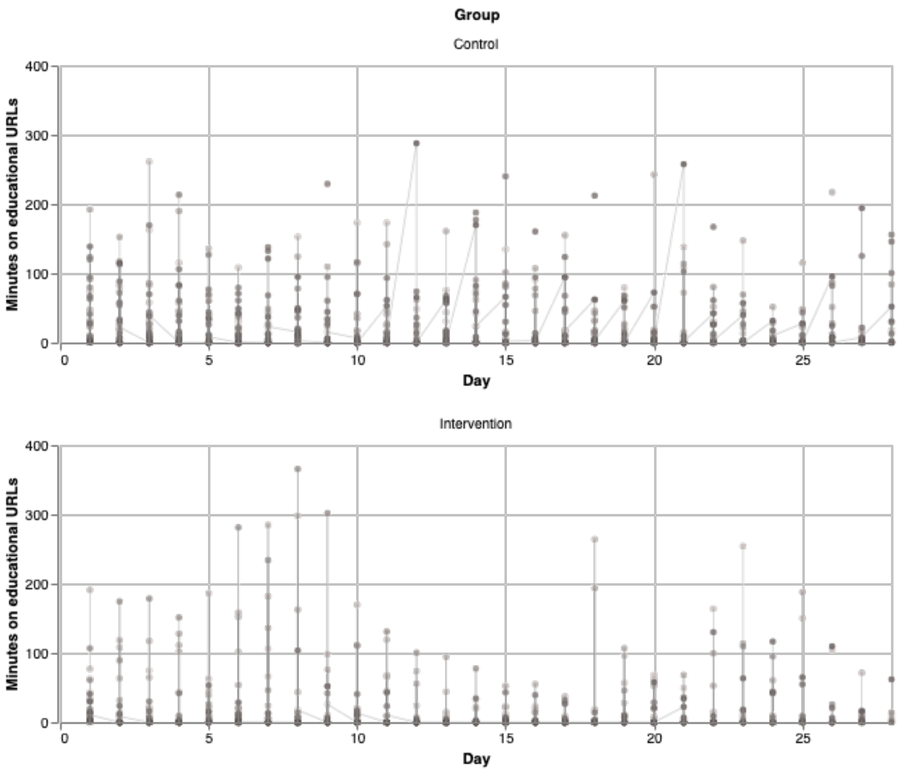


Figure 6.9 Time spent on educational URLs by each individual participant and participants' persistence across days.

5 to 10 — represented as dots with minutes on the y-scale. However, some participants allocated to the control group showed a pattern of regular consecutive sessions, indicated as lines navigating from one dot to another. Overall, this graph demonstrates the relatively frequent regularity of educational web sessions for the participants randomised to the control group, and lengthy performance periods for participants randomised to the intervention group.

As each learner required a different length of time to accomplish their task, time as an absolute value was perhaps not suitable for utilising as a comparable outcome to measure differences in self-regulatory behaviour. In this case, the proportion of time dedicated to educational web resources would be, arguably, a more appropriate outcome for a comparison in the context of learners' self-regulation. To evaluate learners' proportions of time commitment to different categories of web resources, Figure 6.10 was constructed. This graph shows the importance of YouTube and social media websites in learners' daily web navigation behaviour. Nearly half of their total online time was dedicated to these two categories of web resources. The time commitment given to engaging with

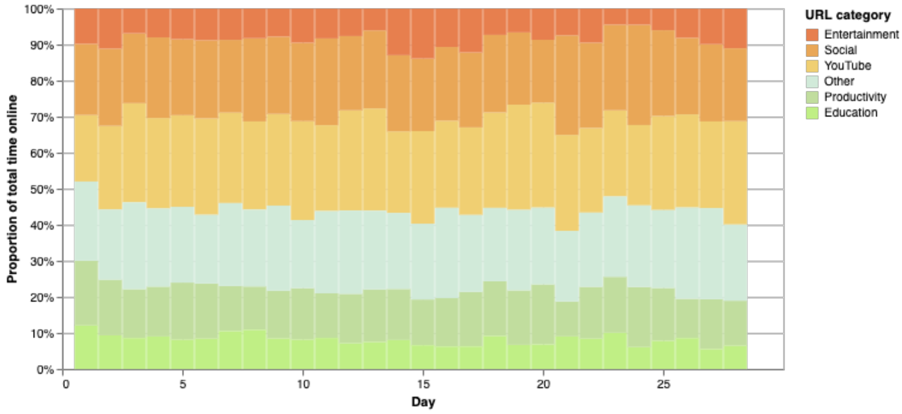


Figure 6.10 Observed learners' time commitment (proportion of total time spent online).

educational websites and resources was categorised as productivity (which might be related to learning as well), and accounted for only a quarter of all time spent online. To continue the examination of time proportions dedicated to different categories of web resources, Figure 6.11 was constructed to visualise behaviour for each participants' group.

Figure 6.11 provides a clue regarding differences in behavioural patterns between groups. It is clear in the figure that the proportion of time dedicated to educational web resources by participants from the intervention group can be described as a wave motion, with two local peaks. There is, further, a distinguishable drop in time dedicated to learning after day 12 until around the third week. The proportion of time dedicated to educational URLs by participants with the basic functionality of the tool remained at roughly the same level during the whole period of the observation. Overall, the time commitment to educational URLs visualised in terms of proportions for each group echoes the patterns observed earlier in absolute values in Figure 6.8 on page 126, and Figure 6.9 on page 128. In addition, this visualisation reveals that the role of web resources related to entertainment was reduced for participants receiving adaptive assistance during the first two weeks. The remaining categories of web resources accessed by participants remained the same across the period of four weeks, with occasional minor fluctuations across time.

The initial exploration of participants' behaviour visualised in graphs can be supplemented by a numerical summary. To provide a summary description of

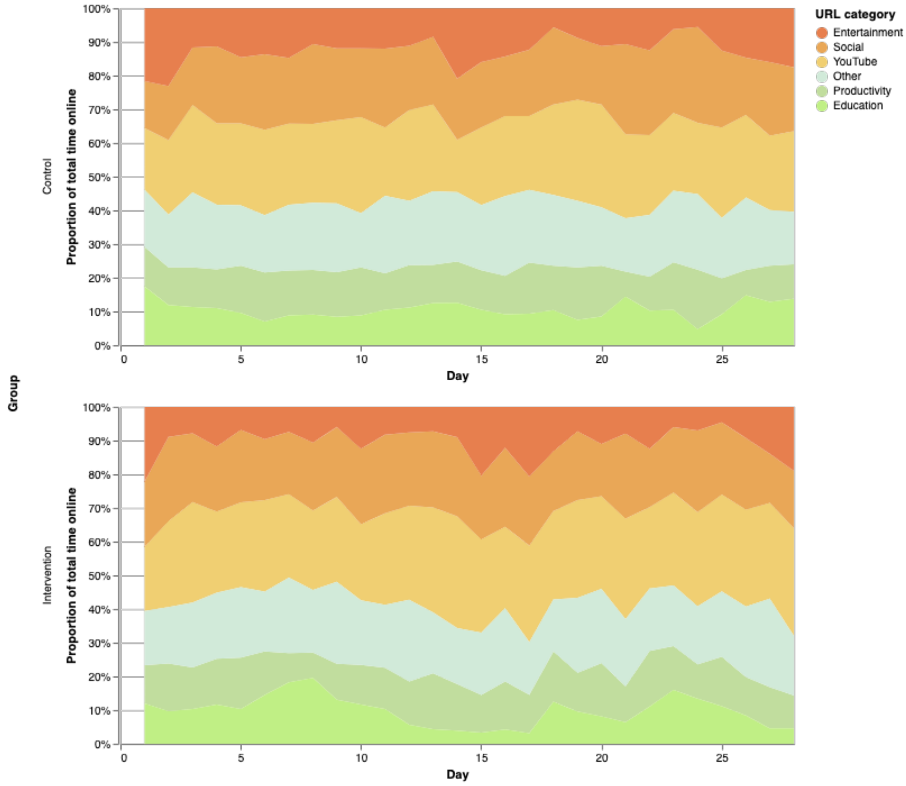


Figure 6.11 Observed learners' time commitment between groups (proportion of total time spent online).

Table 6.11 Summary statistics: participants' daily time spent on six major web domain categories.

	All participants ($N = 134$)			Control ($N = 70$)			Intervention ($N = 64$)			Analysis of diff. b/w groups		
Category	Days w/records	Mean	SD	Days w/records	Mean	SD	Days w/records	Mean	SD	t	p	Hedges' g
YouTube	15.46	49.8	67.8	16.96	51.7	70.3	13.83	47.2	64.4	0.39	0.7	0.07
Social	16.29	40.3	52.6	17.13	43.7	53.5	15.38	36.3	51.2	0.82	0.41	0.14
Productivity	17.47	24.7	39.8	18.40	26.7	40.0	16.45	22.3	39.4	0.64	0.52	0.11
Entertainment	11.25	23.9	53.3	12.03	28.5	59.5	10.41	18.0	43.6	1.17	0.24	0.2
Education	12.30	20.6	43.2	13.19	22.8	42.4	11.33	17.8	44.1	0.67	0.51	0.12
Other	17.29	38.3	52.0	18.20	41.5	57.4	16.30	34.4	44.2	0.81	0.42	0.14
Total time online	17.59	173.1	154.5	18.57	189.3	164.0	16.52	153.1	139.3	1.38	0.17	0.24

collected data, Table 6.11 was constructed. This table includes data showing the learners' average time spent on different categories of URLs. Based on the exploration of data presented in previous graphs it can be assumed that learners committed different amounts of time to educational and entertaining web resources. However, this assumption cannot be confirmed based on the results of conducted t-tests to examine differences in means between groups presented in the table.

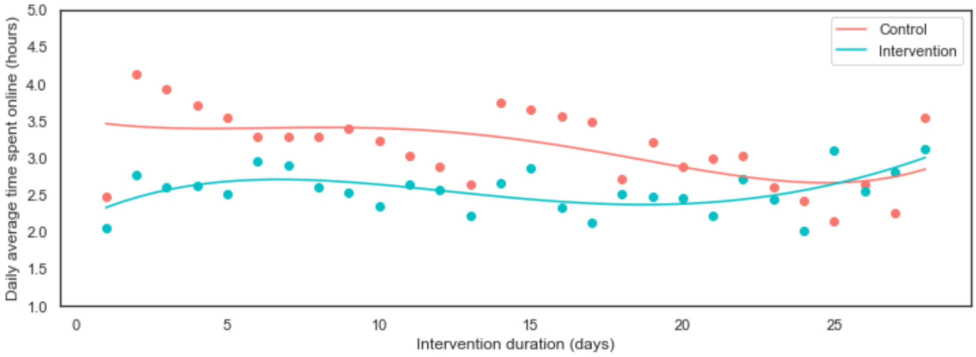
It seems that the average summary cannot represent the full scope of behaviour fluctuations and trends in learners' behaviour across the study period, as shown in the charts provided in Figure 6.11. For example, learners from the intervention group spent a higher proportion of time on their educational URLs at the beginning of their exposure to the intervention, which was followed by a drop in their time attributed to learning, but, crucially, this difference vanishes when the data is averaged across the full length of the study. Therefore, the possibility of the compensatory function of the intervention with a time varying effect should be examined further to reveal the presence of periods when learners' exposure to the intervention provides differences between groups. Given the insights from Figure 6.11, it is unlikely that a standard linear model can accurately represent participants' behaviour, and it should be extended with a polynomial function to construct curves that can be fitted to the time learners from each group spent on different categories of web resources. The resulting curves should ideally highlight any differences in learners' time commitments across the study period.

To fit data with curves that would be capable of accurately representing learners' behaviour across time, a comparison procedure was performed, examining the suitability of fits with a different degree of polynomials. The rationale for this stems from the fact that fitting a linear or quadratic model would not be able to grasp patterns discoveries in Figure 6.11. Fitting curves with a different degree of polynomials, incremented with one degree per step, revealed that the time-varying pattern in learners' behaviour for educational URLs (the main category of interest) was visually distinguishable with at least a four-degree polynomial curve.

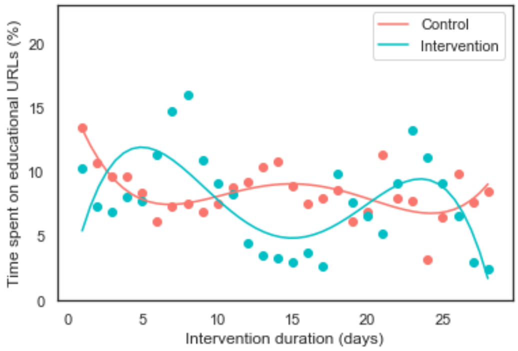
This choice was supplemented by evaluating the sum of squared residuals for each fitting model by modelling polynomial degrees along a range from 1 (linear fit) to 8.

Although other more robust methods can be applied to validate model performance and to choose a suitable regression curve (e.g. the Akaike Information Criterion), at this stage, the results of changes in sums of squared residuals were sufficient to detect an appropriate fit in terms of the number of degrees of polynomials. The squared sum of residuals continued to drop with higher degrees, especially for the intervention group, with a more stable decline after fitting a 6-degree polynomial. The final choice was made in favour of a four-degree polynomial. Applying high polynomial degree coefficients for fitting data is not usually recommended, as it increases the complexity and makes it more difficult to interpret received results (James, Witten, Hastie and Tibshirani, 2013, p. 266), and may lead to issues associated with data overfitting, such as the loss of a curve's grasp to data in the case of removing or adding a new data point. To stay consistent with the chosen polynomial fit model for one category of URLs, the same choice of polynomial degree was applied to other categories of interest. Further, an explorative evaluation of splines fitted to the data (e.g. a natural cubic spline model with 4 degrees of freedom) yielded in visually similar patterns in terms of the proportion of time learners spent on educational URLs. As the aim of these visualisations was in the exploratory evaluation of the presence of time-varying differences in behaviour, a simpler approach that was, nonetheless, sufficient to reveal trends was chosen.

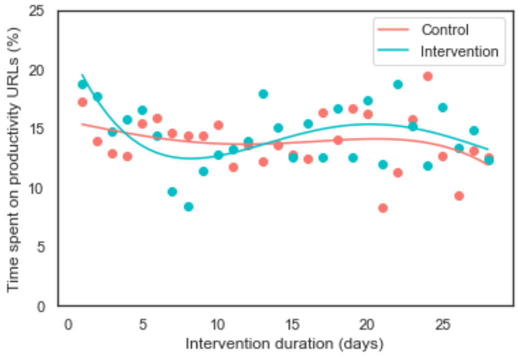
Curves with a least-squares fourth-degree polynomial fit for each category of web domains and learners' time spent online were fitted to the collected data and are presented in Figure 6.12. The graph located at the top of the figure shows that the total time spent online by learners from each experimental conditions was distinct across the study; learners from the control group demonstrated prolonged web activity, compared to participants from the intervention group. The graph on the left panel in the second row shows the difference between curves relating to learners' course websites and other 'educational' URLs. Dots on the graph represent average participants' time on this category of URLs, and may show heteroscedasticity in their outcomes. However, curves fitted to data points suggest that learners exposed to the intervention tended to contribute a higher proportion of their time to learning at the beginning of the intervention than the second half of the study. In contrast, learners from the control group demonstrated a



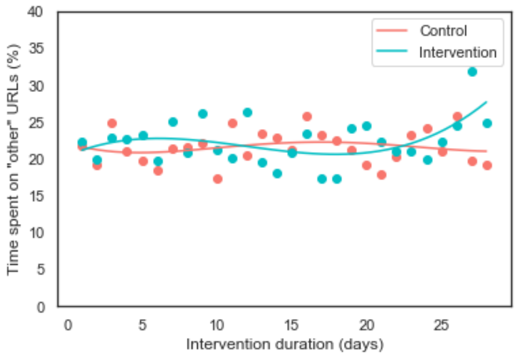
(a) Average daily total time spent online between participants' groups



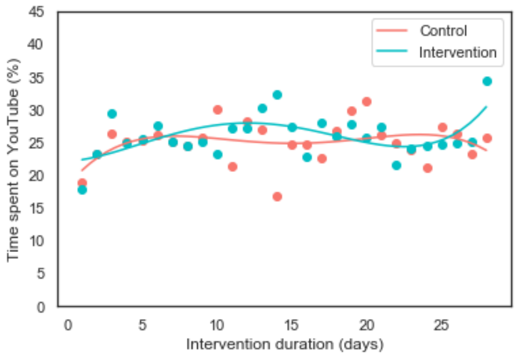
(b) Educational websites



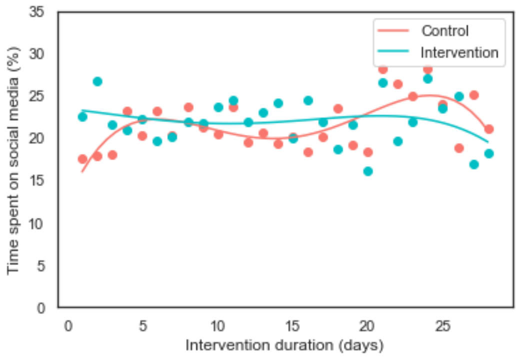
(c) Websites categorised as 'Productivity'



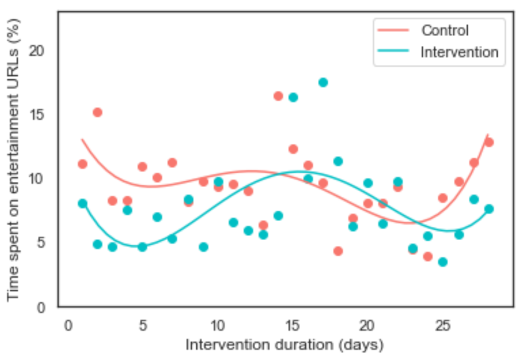
(d) Uncategorised websites



(e) YouTube



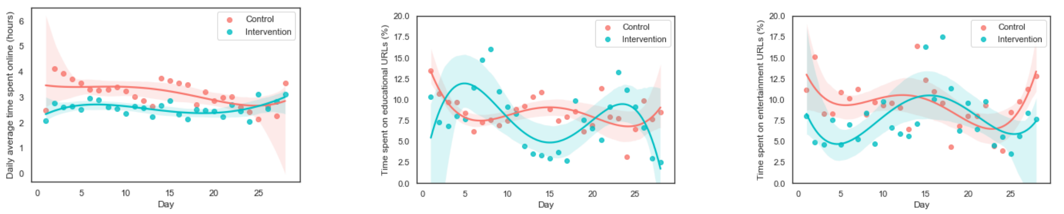
(f) Social media websites



(g) Websites categorised as 'Entertainment'

Figure 6.12 Curves with polynomial fits for each category of web domains.

reduction in the proportion of time committed to educational URLs initially, with an increasing trend towards the end of week two, which was 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. In the first two weeks, the curve that represents learners from the intervention group is noticeably lower when compared to the 'control' curve, as lines at this point start to behave symmetrically. It can be noted from the figure that the observed behaviour between the groups is nearly identical for other categories of URLs, such as Productivity, YouTube, Social media, and Other websites. The confidence intervals presented in Figure 6.13 were computed for the curves where differences between groups were observed. 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.



(a) Total time online (b) Educational websites (c) Entertainment websites

Figure 6.13 Confidence intervals for curves fitted to behavioural data.

To examine whether participants' exposure to the intervention corresponded to shifts in their behaviour, the frequency of the number of occurrences of decision points that triggered the intervention, and the number of times participants were exposed to the mechanism of the intervention (through notification messages) can be compared with the proportion of time learners spent on educational web resources. The adaptive intervention consisted of decision rules and was triggered by signs of procrastinatory behaviour (as described in Figure 5.4 on page 97), and the occurrence of these decision rules was recorded for both groups of participants. Across web domains, moments when a learner spent at least five minutes on a website categorised as 'entertainment', or at least 16 minutes on any other website (except those categorised as productivity, or an indicated course website) were recorded as decision points and saved to the app database. In total, 2,717 decision points were recorded. Some example of web URLs, where learners' procrastinatory behaviours were frequently occurred, include: social media websites, such as facebook.com (742) and web.whatsapp.com (41); video streaming services, such as youtube.com (486), dadiscordapp.com (160), netflix.com (113), and primevideo.com (55). Therefore, the frequency of failures of self-regulatory behaviour expressed in the number of decision points, and the intensity of the intervention, expressed in the number of displayed notifications, can be examined in relation to observed participants' behavioural shifts, i.e. the proportion of time learners spent on educational URLs.

The process of this examination can broken down into two steps. First, although participants from the control group did not receive the intervention, every time their behaviour was considered procrastinatory, the need for intervention (a decision point) was recorded in the tools' database. Second, as only participants from the intervention group received the adaptive intervention, and the probability of receiving an assigned intervention at each decision point was set at 50% (as illustrated in Figure 5.4), recorded decision points and the recorded events of intervention delivery can be displayed separately. This separation, inherent in the study design, allows the intensity of the intervention (expressed in the frequency of delivered notification messages) for the intervention group to be examined, as well as the frequency of procrastinatory behaviour for both groups. Furthermore, it allows for the examination of learners' behaviours in response to intervention within the intervention group, through a series of intraindividual randomisations. Comparing data, as described, allows the role of adaptive assistance contributed to developmental and compensatory shifts in behaviour to be examined. To map these data and its possible relationships, Figure 6.14 was constructed.

In Figure 6.14 the shaded areas filled with colours (in the background of the chart) represent the proportion of time participants from each group spent on web resources categorised as educational. This figure repeats data provided in Figure 6.11 on page 130. The colourful lines indicate the average occurrence of decision points for each group (i.e. the number of times behaviour resembling a failure of self-regulatory behaviour occurred and when a notification should be displayed to

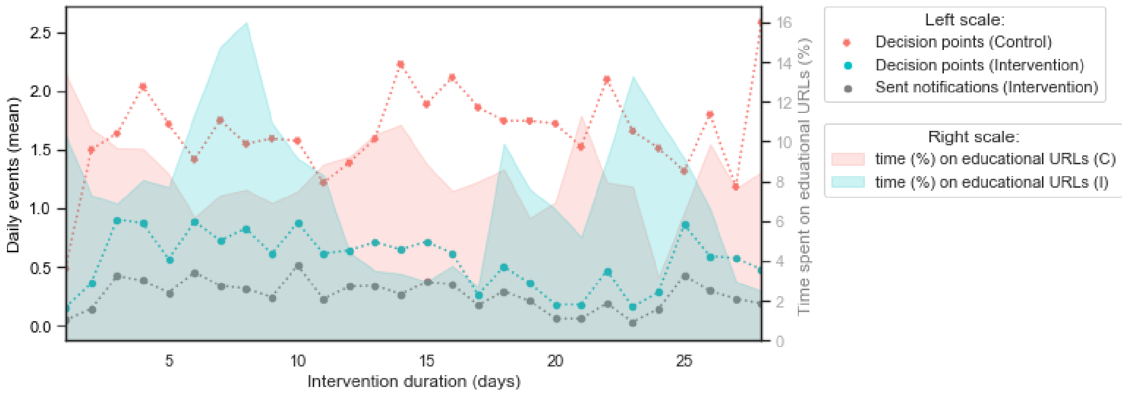


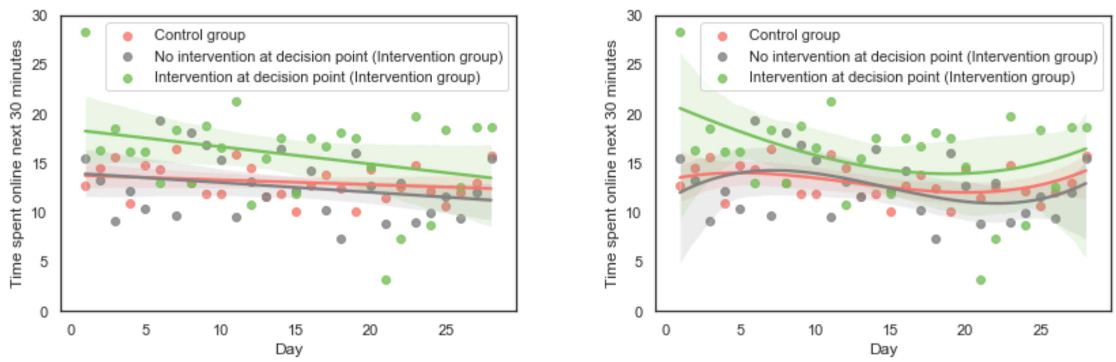
Figure 6.14 Relationship between events that triggered the adaptive assistance, notifications shown, and the proportion of time spent on educational web resources between groups.

a participant). The grey line indicates the actual number of displayed notifications to participants from the intervention group (as mentioned earlier, only participants from this condition received notifications with the probability of 50%). Lines refer to the left scale, and shaded areas relate to the right scale. The next example illustrates the information provided in this graph. On the fifth day using the virtual assistant, on average, the proportion of time spent on web resources related to learning was around 8% for participants from both groups. On this day, participants from the control group demonstrated procrastinatory behaviour (expressed in the number of decision points recorded) on average 1.7 times, while participants from the intervention group manifested these behaviours 0.6 times. Participants from the intervention group received 0.3 notifications on average during the fifth day. The total number of notifications displayed on this day was 13. The total number of decision rules recorded and notifications sent on a particular day can be derived through the average numbers provided in this graph and the number of unique daily participants provided in Figure 6.7 on page 122. Given the information about participants' attrition during the time-frame of the study, the left panel of Figure 6.7 provides web session activity recorded on day 5 for 46 unique participants allocated to the intervention group. Therefore, on the standardised day 5, 26 decision points were recorded for the participants from the intervention group, and 13 notifications were displayed by the assistant, distributed among the 46 total participants. For the participants allocated to the control, 91 decision points were recorded among 53 participants.

Two noticeable distinctions between groups can be observed from this graph. First, learners from the intervention group accumulated less recorded events relating to the failure of self-regulatory behaviour (expressed in the number of decision points), in comparison to the control. Second, the number of decision points is gradually reducing over time for the intervention group. Adding these two discoveries to the observed proportion of time spent on educational web resources (filled areas), it can be noted that despite decreasing the intensity of the intervention, participants allocated to the intervention group demonstrated an increase in the proportion of time committed to educational web domains during the second half of the third week. This trend could indicate an increasing effectiveness in compensation occurred in learners allocated to the intervention group. However, as can be noted from the results of the evaluation of the development effect of the intervention, as presented earlier, there was no statistically clear evidence to support this claim. Speculatively, one possible interpretation of this is that self-report questionnaires might not be as sensitive towards developmental changes in participants' behaviour.

An overview of daily decision points, the intensity of the intervention, and the amount of time allocated to learning was provided in Figure 6.14. However, a daily time window could be an excessively long time-frame to effectively associate the compensatory function of the intervention and observed learners' behaviour. Participants' exposure to the intervention and learners behaviour should be explored at a more granular level of detail in order to determine the presence of any short-term compensatory effects offered by the intervention.

To achieve this, two proximal outcomes were selected: the total time spent online and time spent on educational web resources in subsequent 30 minutes after a decision point. The 30 minute time window was selected as one of the decision rules underpinning the adaptive assistance was set not to display a notification more often than once in 30 minutes (see Figure 5.4 for more details about the decision rules implemented in the adaptive assistance intervention). Therefore, the 30 minute time-frame avoids any overlap between notification messages in the outcomes. The applied repeated micro-randomisation of delivery versus not delivering the intervention at a decision point within the intervention group provides an additional layer of support for any possible findings of differences between the control and intervention groups. It allows the short-term compensatory effect of comparing proximal outcomes to be examined as follows: first, within the intervention group (delivered versus not delivered), between delivered intervention for the intervention group versus the control, and between not delivering an intervention and the control group.



(a) Linear regression fits

(b) Fits with a three-degree polynomial

Figure 6.15 Curves with linear and polynomial fits for the total time spent online between and within groups.

To examine participant's behaviour following a decision point, the total time spent online and time spent on educational URLs in the 30 minutes following a decision point was averaged after grouping by participants and standardised days since enrolment. Linear and polynomial curves were fitted to resulting data points, together with their confidence intervals for each group of learners. The results of this procedure are visualised in Figure 6.15. Distinguished trend lines can be observed in this figure. Curves fitted to the resulting data and their 95% confidence intervals suggest that exposure to the intervention, on average, tended to an increased amount of time spent online in the 30 minutes following the intervention. The time varying effect of this trend is explored further in Figure 6.16.

As seen in Figure 6.16, participants allocated to the intervention group who did not receive a notification showed a similarity with participants from the control group in their time spent online following a decision point. However, participants from the intervention group demonstrated more time online after receiving a notification

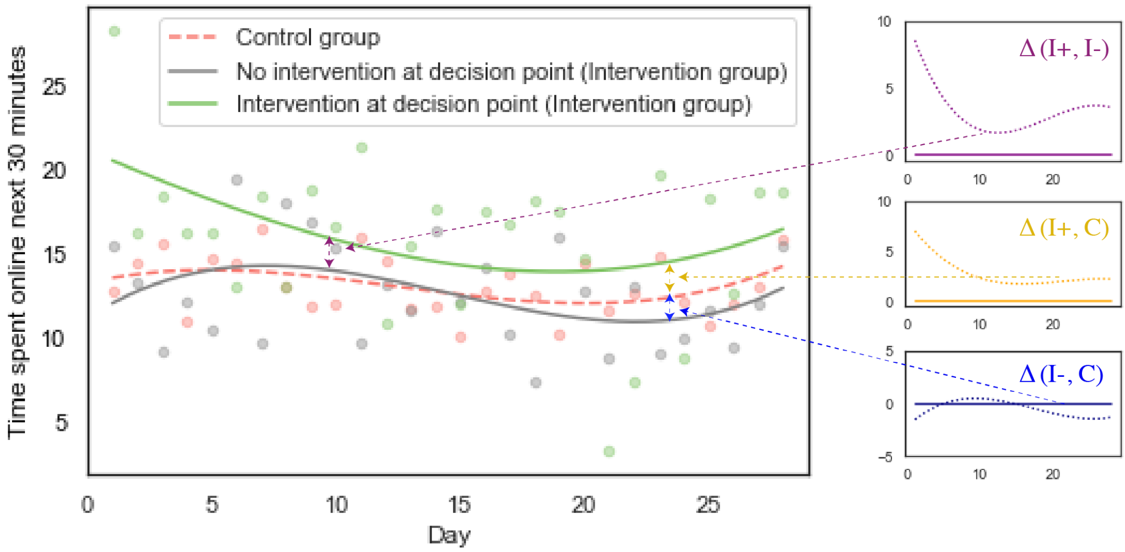
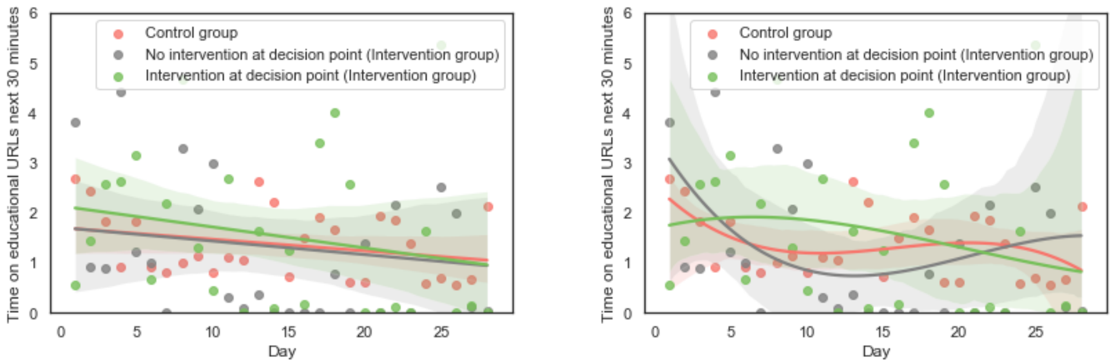


Figure 6.16 Curves with polynomial fits for the total time spent online between and within groups.

after a decision point. The time-varying difference of this effect is displayed in graphs to the right side of Figure 6.16. The top-right chart illustrates changes in curves between receiving versus not receiving the intervention after a decision point for participants allocated to the intervention group (Δ(I+, I-)). The middle right graph shows the time-varying difference for participants assigned to the intervention group when they received the intervention, compared to participants allocated to the control (Δ(I+, C)). The bottom right chart shows the time-varying difference between participants allocated to the intervention group in the event that they did not receive the intervention, compared to participants assigned to the control group (Δ(I-, C)). To conclude, participants' exposure to the intervention is associated with an increase in their overall time spent online in the next 30 minutes after a decision point by up to seven minutes at the beginning of the study, gradually decreasing over time, extending the total time spent online by two to three minutes on average after day 10. However, these findings are exploratory, and causality cannot be inferred from these results.

As mentioned earlier, the same procedure described above was applied to the proximal outcomes, in terms of participants' time spent on educational web resources in the 30 minutes following a decision point after receiving or not receiving an intervention. The results obtained were visualised and provided in Figure 6.17. This figure shows that curves for each participant group fitted to the resulting data are not distinguishable, and their 95% confidence intervals overlap throughout the whole study period. Therefore, it is statistically unclear if providing the intervention helped learners to compensate for a lack of self-regulation in the short-term period and spent more time on their courses and educational web resources following procrastinatory events.



(a) Linear regression fits

(b) Fits with a three-degree polynomial

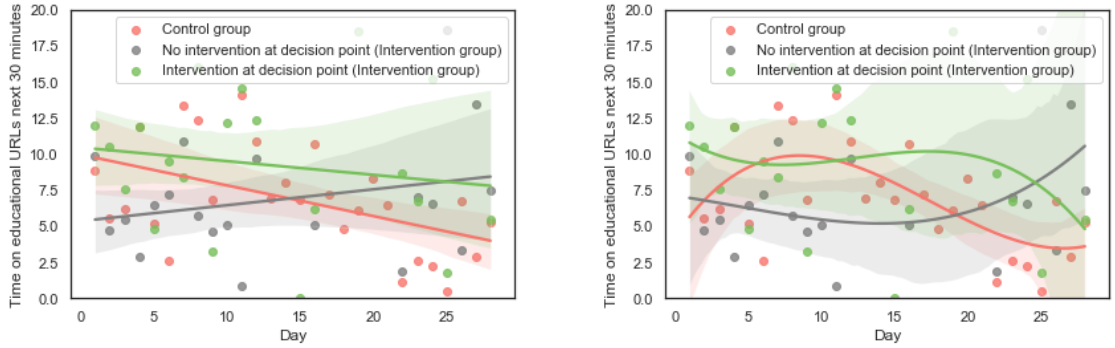
Figure 6.17 Curves with linear and polynomial fits for participants' time spent on educational web resources between and within groups.

Results presented in these graphs and in the previous exploratory evaluations of time commitment levels following decision points should be interpreted with care, as the adaptive assistance was triggered by learners' behaviour, rather then pre-specified timely intervals. For example, a notification sent during a procrastinatory behaviour which occurred before a learning session would be likely to result in a more prolonged learning session, rather than a notification sent during procrastinatory behaviour, which might happen immediately after another learning session during the same day. Such contextual nuances can be taken into account as a covariate, as it was implemented in the micro randomised trial to optimise the intervention to promote physical activity (measured using a wearable activity tracker) in the HeartSteps study (Klasnja et al., 2019). In their study, the proximal effect of the intervention was expressed in daily step count and measured during a 30 minutes time interval following the intervention, and then adjusted for step count during a 30 minute interval prior to a decision point (Klasnja et al., 2019, p. 577). Further, in the present study the chosen time-frame for the proximal outcomes covers a limited part of learners' subsequent behaviour. However, encompassing a wider time window has its limitations, as it requires an additional analytical strategy to exclude the overlapping effect of several interventions.

Overall, the exploratory evaluation of behaviour traces suggests that participants' exposure to the intervention demonstrated mixed results. On the one hand, their total daily time spent online was shortened in contrast to participants from the control group in the first three weeks. On the other hand, their short-term behaviour, in terms of total time spent online in the 30 minutes interval following a delivered intervention, was longer than for participants from the control, and in the case of undelivered interventions. Participants from the intervention group showed an increased amount of time spent on educational resources, and a reduced time commitment to URLs categorised as entertainment web sites in the first 10 days after exposure to the intervention. Overlapping confidence intervals of curves fitted to data suggest that there is no evidence that this pattern was retained in the short-term effects after delivering the intervention. These results may suggest that the intervention was helpful for learners during the first 10 days, but the positive effect of the intervention reduced over time. One possible explanation for this shift in observed behaviour is the novelty brought to the learners' web environments by the adaptive assistance tool and its notification messages, which naturally reduced as participants became more familiar with it.

The intervention provided to participants allocated to the intervention group constituted of assistance provided when participants were in need, and encouragement to continue a learning session. Previous exploratory examinations focused on the assistance provided through web resources that were not indicated by learners as their online course website. Figure 6.18 offers a visualisation of the role of notifications provided when learners had spent at least 25 minutes on their indicated online courses.

This graph enables an examination of the extent to which assistance provided during a study session may be helpful to extend a learning session further. More specifically, this figure was examined to reveal to what extent encouraging notifications displayed to participants from the intervention group during a study session (after at least 25 minutes spent on an indicated course URL) resulted in



(a) Linear regression fits

(b) Fits with a three-degree polynomial

Figure 6.18 Curves with linear and polynomial fits for participants' time spent on educational web resources after receiving notifications relating to their online course, following a 25 minute learning session.

the extension of the learning session. Figure 6.18 shows that participants' web activity on educational URLs generally began to decline after two weeks, as can be seen from the red curve in the right side chart. Comparing the curves within the intervention group (with delivered intervention — green line, and not delivered intervention — grey line) suggests, at least informally, that encouraging messages are helpful up until the third week, after which it is more beneficial to remove them. However, the efficacy of the intervention in this case cannot be distinguished with certainty, as a result of the high variability in the collected data and the overlapped 95% confidence intervals for the curves fitted to the data.

In order to examine the effect of individual notifications, categorised according to their behavioural change techniques, data collected with summary records detailing the occurrence of behaviours that trigger adaptive assistance (decision points), alongside the interventions themselves, are considered in the rest of this section. A subset of these data (together with the applied classifications of the intervention's components) is illustrated in Table 6.12.

Table 6.12 provides an example of recorded decision points and participants' responses to notifications triggered by pre-set rules and randomisation settings. Each row of the table indicates the occurrence of a decision point when a participant's behaviour met pre-specified rules, and an intervention should, then, be sent. The column 'Notification Sent' indicates if a notification was sent to a participant or not.

Table 6.12 Example of recorded decision points and responses to adaptive assistance notifications.

UserId	Status	URL visited	Timestamp	Notification Sent	Group	Day	Behaviour Change Technique
9586920e	1	facebook.com	2019-10-01 13:49:37	1	Intervention	4	4.4. Behavioural experiments
ec1de6ac	0	facebook.com	2019-10-01 19:10:23	0	Control	2	2.2. Feedback on behaviour
ec1de6ac	0	facebook.com	2019-10-01 19:44:17	0	Control	2	5.3. Information about social and environmental...
295a3f28	0	facebook.com	2019-10-01 19:20:10	0	Intervention	2	10.8. Incentive (outcome)
31ddcc19	0	facebook.com	2019-10-01 18:24:03	1	Intervention	9	5.6. Information about emotional consequences
ec1de6ac	0	facebook.com	2019-10-02 00:22:51	0	Control	3	2.7. Feedback on outcomes of behaviour
bdf86516	0	facebook.com	2019-10-02 10:46:51	0	Intervention	3	2.7. Feedback on outcomes of behaviour
debf3c2a	0	facebook.com	2019-10-02 10:44:16	0	Control	3	2.2. Feedback on behaviour
bdf86516	0	facebook.com	2019-10-02 11:19:19	0	Intervention	3	2.4. Self-monitoring outcomes of behaviour
56553b82	0	facebook.com	2019-10-02 11:50:32	1	Intervention	2	2.5. Monitoring behavioural outcomes without...

For participants from the control group, this column consists of zeroes, as this group was not offered adaptive assistance. Nonetheless, the occurrence of decision points were recorded. For participants allocated to the intervention group, the intervention was provided with the probability of 50% at each decision point, and in the event of providing an intervention at this particular point of time, a notification template was chosen randomly, among a set of pre-designed and manually coded templates. Even in the event of not providing an intervention and not delivering a notification to a learner, the decision point, together with a randomly assigned notification template, was recorded in the database. Values of ‘1’ in the column ‘Notification Sent’ indicates that the assistance was sent to a participant; ‘0’ indicates otherwise. The column ‘Day’ represents the standardised date of the participants’ enrolment in the study. The column ‘Timestamp’ indicates the date and time when a participant should receive a notification (regardless of whether it was sent to a participant). The column ‘URL visited’ represents the domain name the participant was using when the decision point occurred, and where the participant should have been received the intervention. The column ‘Status’ indicates the participant’s direct response to the intervention: ‘1’ in cases where the participant clicked on the button (provided together with a notification), which leads to opening a new web browser tab with the participant’s course web page (provided earlier by the participant on their goal-setting webpage of the assistant) or a pre-specified web URL, such as a link to the project website with a learning analytics dashboard, illustrating the participant’s behavioural data (described in Section 4.5). Otherwise, if the participant rejected an intervention and clicked on the button ‘now now’, a ‘0’ was recorded.

The following example neatly illustrates the data collection procedure for individual components of the adaptive intervention, using the repeating micro randomisation data structure: when a learner spent 10 minutes on facebook.com, it was assumed that the learner was demonstrating procrastinatory behaviour, and would benefit from an intervention. This moment was then saved in the app database as a decision point. At this decision point, a message template from a list of pre-designed templates was randomly chosen. Then with a 50% probability of sending or not sending a notification (it was 0% probability for participants allocated to the control group), the learner received a randomly chosen message template. The results of this randomisation, alongside the metadata regarding the selected template, were saved in the app database. In cases where the notification was sent to the learner, their immediate response (to accept or decline the notification) was recorded. If the notification was not sent, a '0' was entered into the database.

The design of this data structure was guided by principles applied to micro randomised trials (for more details, see Klasnja et al., 2015). This design allows the time participants spent online after receiving/not receiving a notification to be displayed. Figure 6.19 provides information on differences in participants' responses to the intervention components (notification messages), categorised according to their behavioural change techniques. Figure 6.20 provides the difference in the total time spent online in the 30 minutes following a decision point between the notifications displayed to participants in the intervention group and participants from the control group (coloured in red). Figure 6.21 illustrates the difference in the proximal outcome between displayed versus not displayed notifications within the intervention group (results for not delivered notifications appear in black). Orange bars represent BCTs with no overlapping confidence intervals for their proximal outcomes, with at least five notifications delivered. Horizontal lines on these figures represent the average time spent online across all considered BCTs and their confidence intervals for delivered (green line) and not delivered (black line) notifications within the intervention group and the control group (red line). The number on each bar provides the number of records for each BCT for each category analogously (delivered, not delivered, and control).

Horizontal tick marks on bars show the means for each BCT of notification templates for each considered condition (delivered, not delivered, and control).

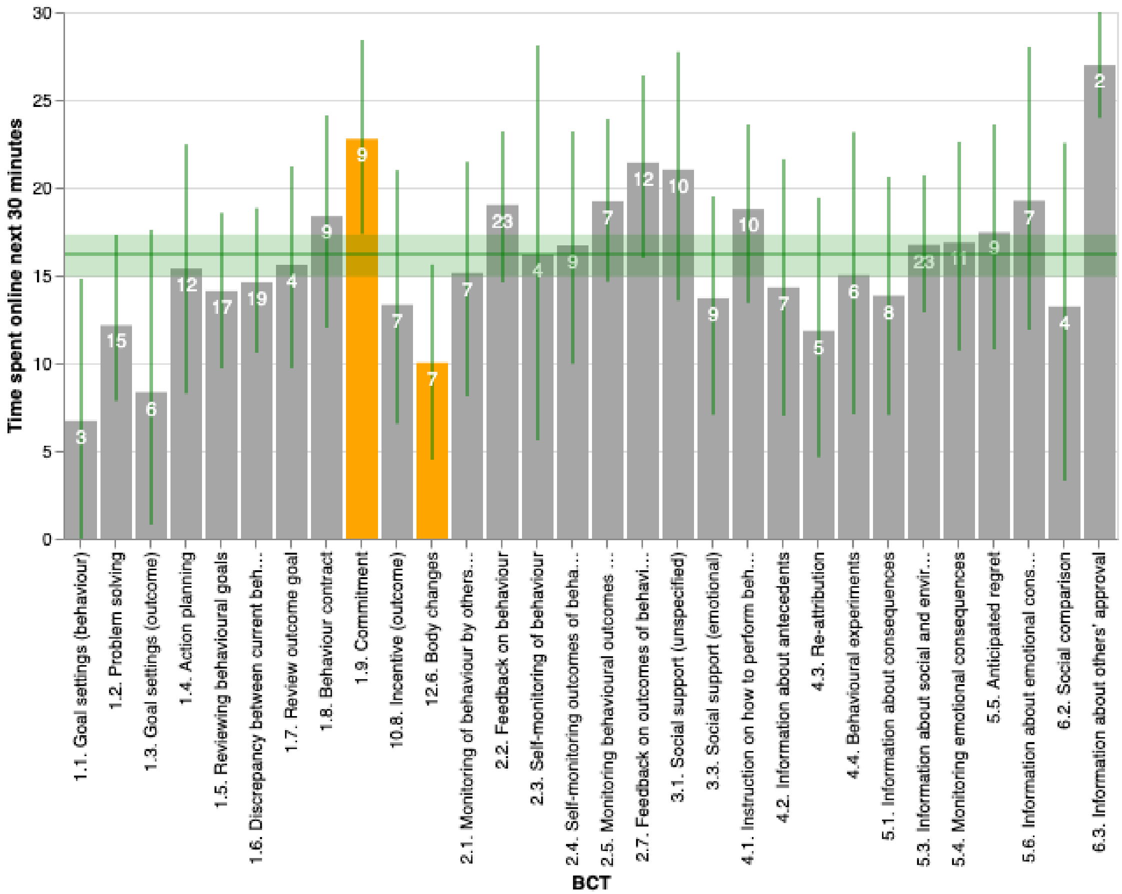


Figure 6.19 Participants' behaviour in response to displayed adaptive assistance notification messages.

It is important to note that due to the applied research design of this study, the number of decision points for each participant was not consistent across time, as the intervention was driven by participants' behaviour rather than by a pre-specified number of notifications displayed per day for each participant. Further, the probability of the delivery of notifications was set at 50%, which resulted in an actual ratio of delivered notifications of 47%. As can be seen in Figure 6.19, due to the unequal number of notification templates for each category of BCTs and their random selection, the frequency of their delivery differs.

Although the resulting dataset does not allow for causality regarding the difference in effectiveness of the intervention's individual components to be inferred, the data structure and recorded proximal outcomes are nonetheless

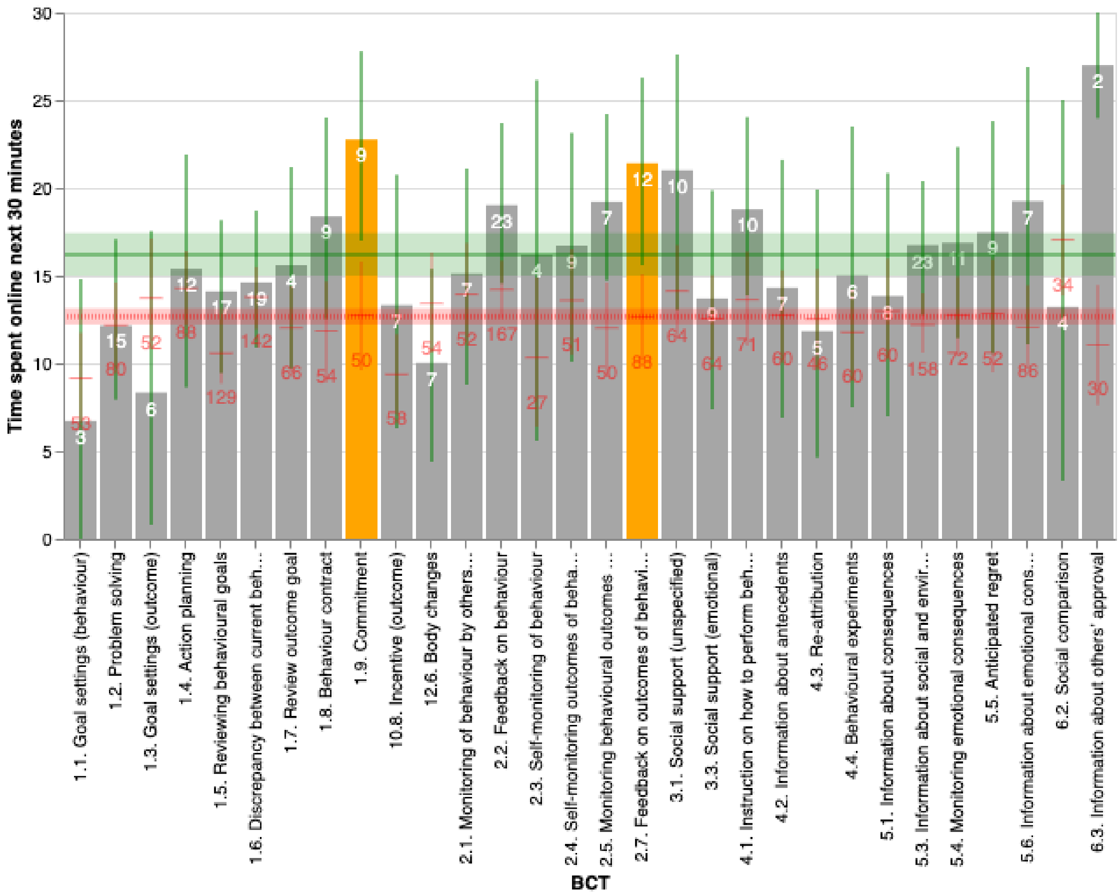


Figure 6.20 Participants' behaviour in response to displayed adaptive assistance notification messages, in comparison with not displayed notification messages (control group).

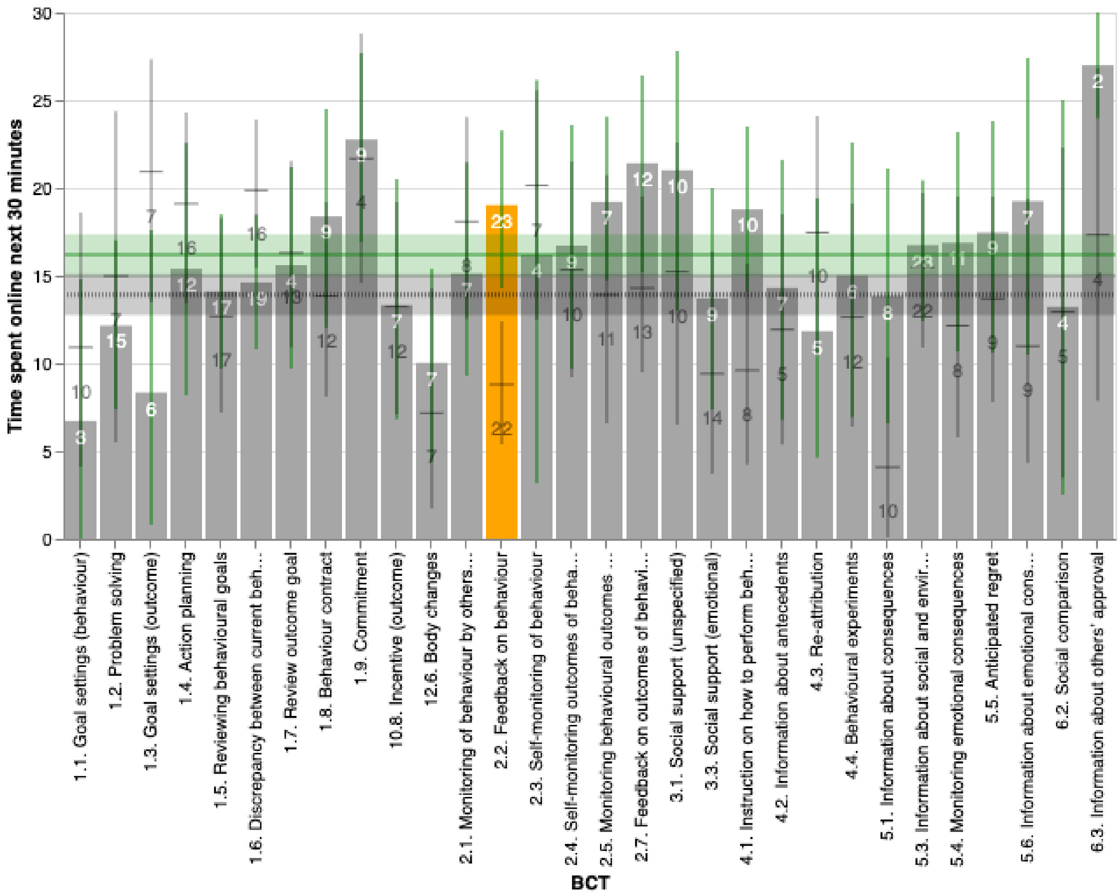


Figure 6.21 Participants' behaviour in response to displayed adaptive assistance notification messages, in comparison with not displayed notification messages (intervention group).

valuable. The data set offers possibilities for future exploratory evaluations of the differential role of adaptive assistance components on the proximal outcome. This provides a starting point for further examination, with the potential to be extended by implementing inferential approaches to evaluating the data (see, for example, up-to-date data analysis methods to evaluate data from MRT in Qian et al., 2020).

As the figures demonstrate, for some notification messages categorised according to their behaviour change techniques, proximal outcomes deviated from the average combined across all BCTs — this can be observed in the orange bars. However, the orange bars operate differently in these three figures, depending on the variables selected for comparison. In Figure 6.19, this comparison is based on how the mean average time spent online for some BCTs of displayed notifications deviates from the average time across all BCTs of the notifications displayed. In Figure 6.20, this difference is based on a comparison between the proximal outcome of the displayed notifications and the outcomes for the control group (with no displayed notifications). In Figure 6.21, the comparison is based on outcomes within the intervention group, where the mean average time learners spent online after a decision point in the case of a displayed notification is compared to the same proximal outcome in the case of not displayed notifications. The same principle can be applied to the data relating to notification messages, aggregated to functions of their BCTs, with one level up-line of categorising notification templates. Figure 6.22 illustrates this aggregation with horizontal lines marking each condition (green for displayed notifications and black for not displayed notifications within the intervention group, and red for the control group). For clarity, in this figure, the confidence intervals for the proximal outcomes of each function are only provided for displayed notifications. The main takeaway from these visualisations is that applying a micro-randomisation procedure to the research design, in addition to the standard randomisation of participants into experimental conditions, could provide an extra layer of support when examining the effects of an intervention in order to optimise its components.

In conclusion, the outcome of this section suggests that the utilisation of a virtual learning assistant that provides adaptive assistance has time-varied effect and can

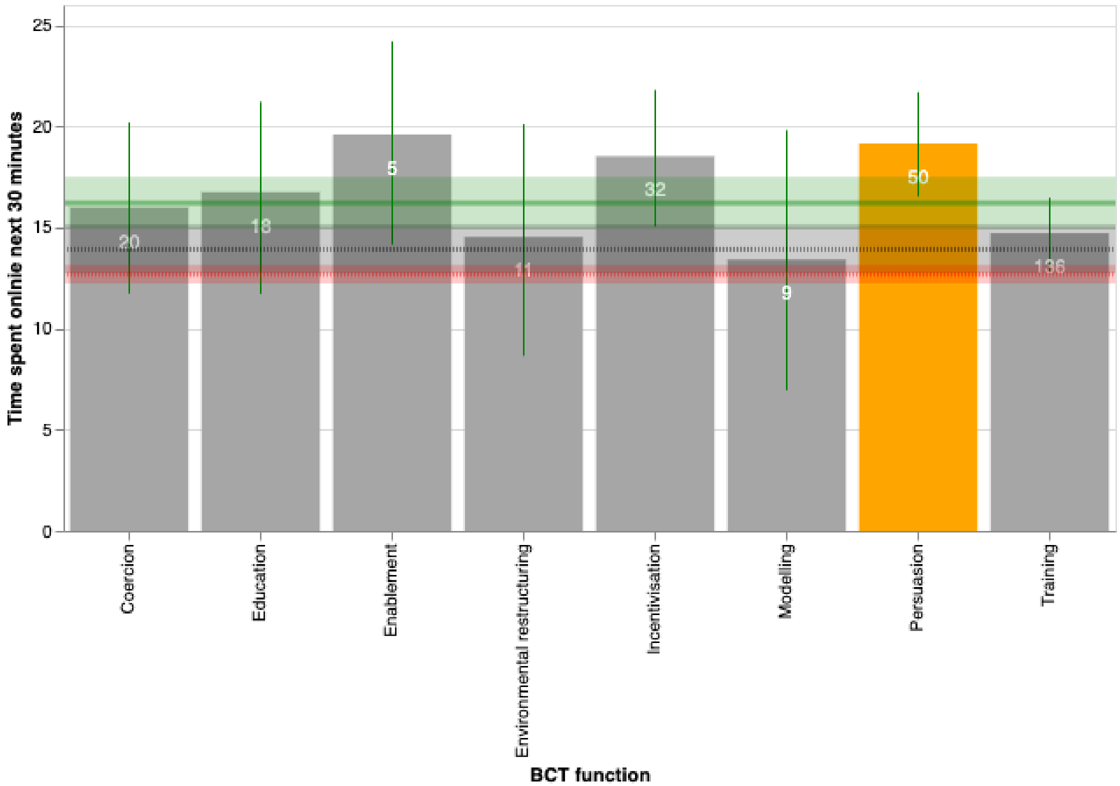


Figure 6.22 Participants' behaviour in response to displayed adaptive assistance notification messages grouped by their function, in comparison with not displayed notification messages.

be effective in compensating for self-regulatory skills, to some extent, as learners allocated to the intervention group spent less time online per day in first three weeks of being exposed to the adaptive assistance, reduced their time commitment to entertainment websites during first two weeks, and increased their engagement with educational web resources during the first ten days.

6.4 The role of individual differences in responses to intervention

This section aims to answer the third research question, regarding the role of individual differences in compensatory and developmental shifts in self-regulation of learning. To examine the role of individual differences in learners' responses to the intervention two approaches were applied. First, univariate repeated measures tests were applied to examine developmental outcomes. Second, visualisations of learners' time allocations to different categories of web resources were utilised as behavioural indicators of potential compensatory changes. The results of a series of univariate repeated measures tests, used to evaluate the role of Agreeableness and Consciousness on participants' developmental outcomes, did not reveal significant results when participants were grouped according to scores of above and below median values. However, to explore the tendencies of developmental shifts in relation to participants' levels of personality traits, visualisations were created. Results are visualised in Figure 6.23 for Agreeableness, while Figure 6.24 shows results for the role of Consciousness in developmental shifts. To examine the role of self-report baseline levels of self-regulation and personality traits on learners' compensatory responsiveness to the intervention, Figure 6.25, Figure 6.27, and Figure 6.26 were constructed. The decision to select Conscientiousness and Agreeableness for the detailed evaluation was driven by a common acknowledgement of associations between agreeableness and learners' susceptibility to providing feedback, with conscientiousness as a predictor of learners' task perseverance (Poropat, 2009). Additional visualisations to examine possible associations between other personality traits and observed learners' behaviour are provided in Appendix E.

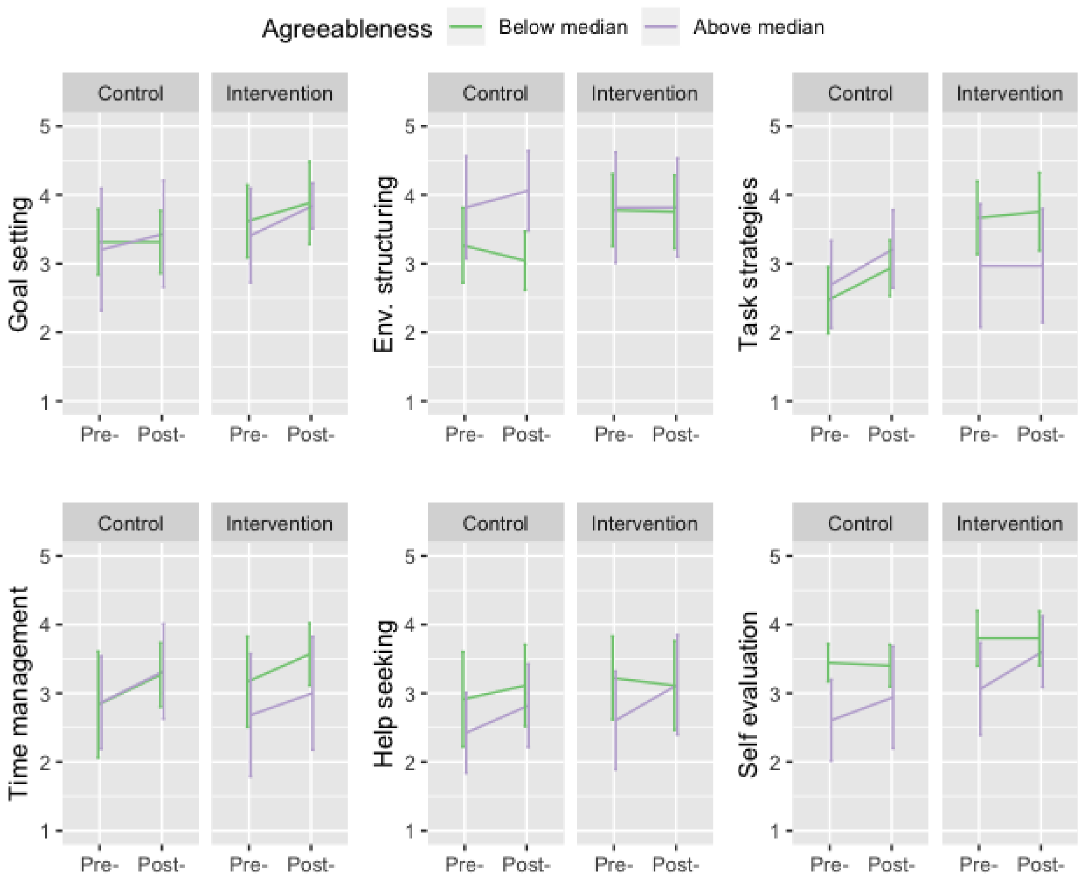


Figure 6.23 The role of the ‘Agreeableness’ personality trait in the developmental shifts in learners’ self-regulation.

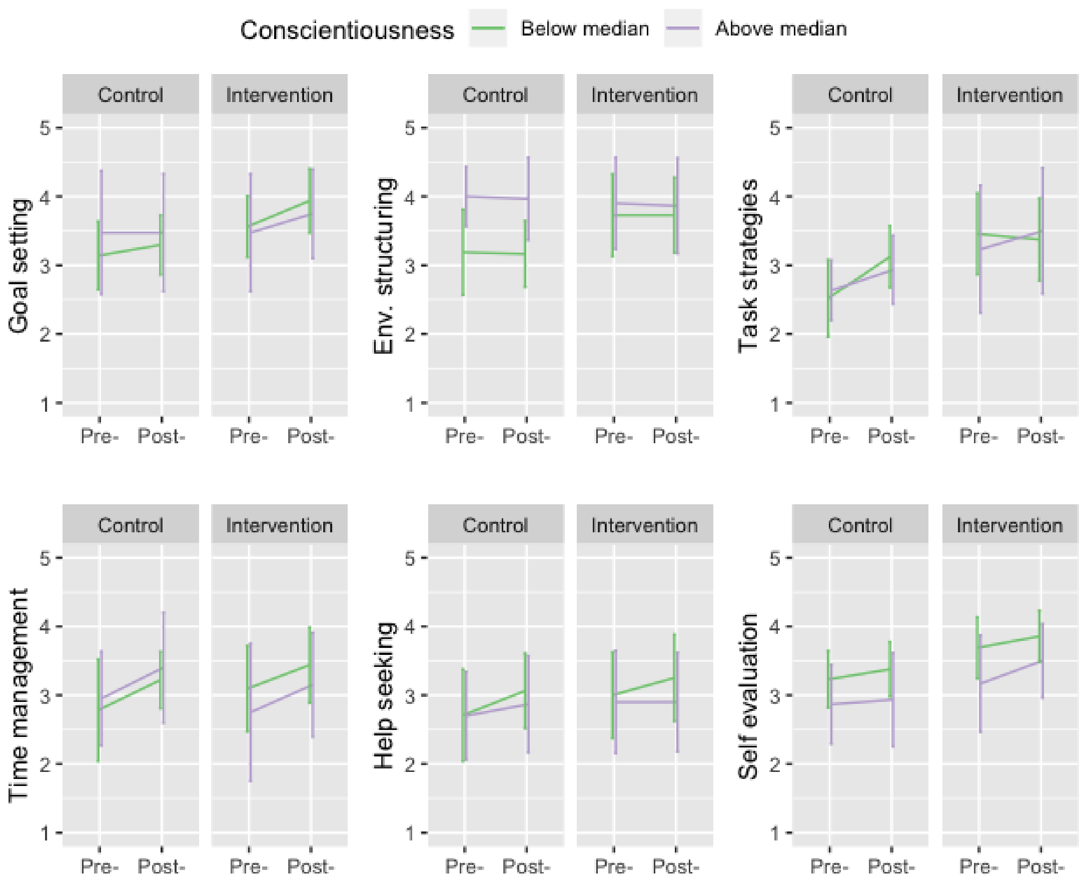


Figure 6.24 The role of the ‘Conscientiousness’ personality trait in the developmental shifts in learners’ self-regulation.

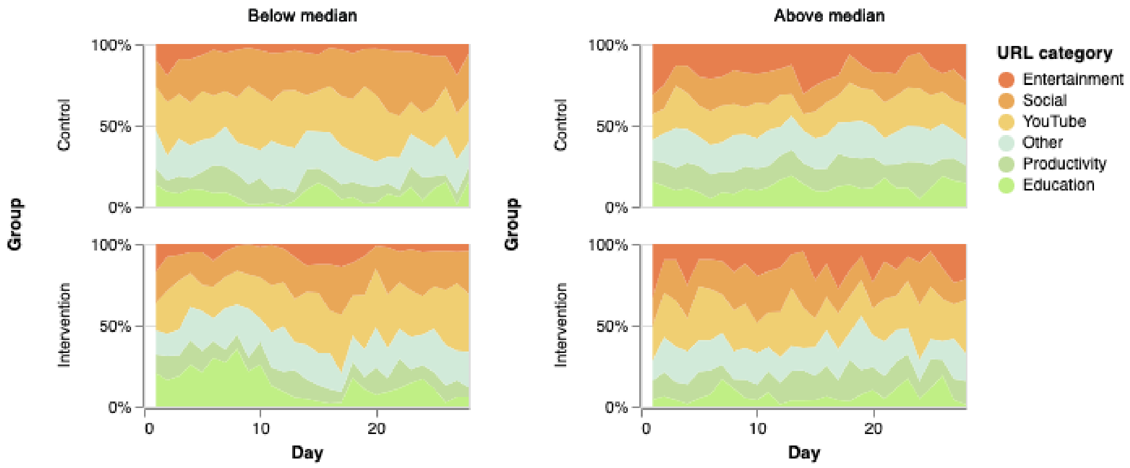


Figure 6.25 The role of pre-intervention differences in overall self-report levels of self-regulation in behavioural shifts in learners' self-regulation.

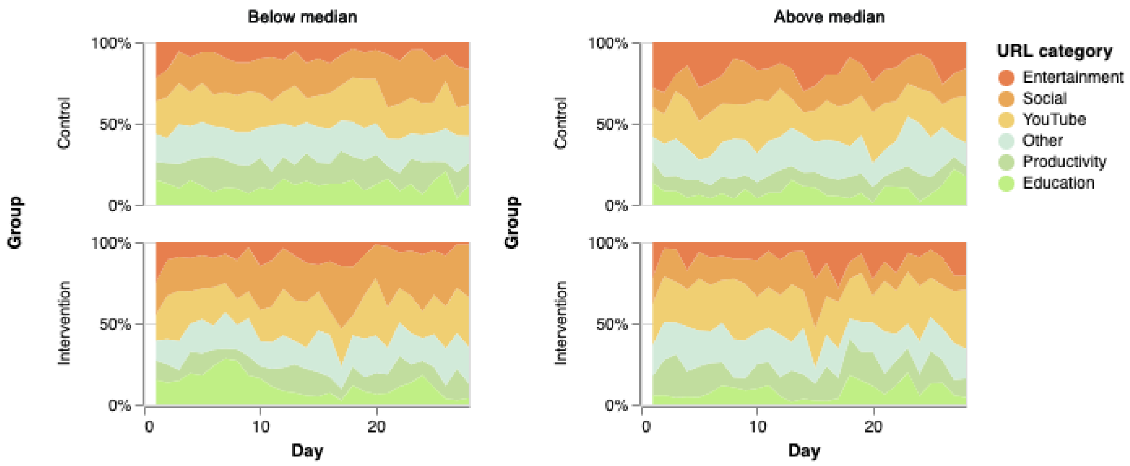


Figure 6.26 The role of the 'Conscientiousness' personality trait in behavioural shifts in learners' self-regulation.

Figure 6.25 shows that learners with scores above the median of the sample in self-report levels of self-regulation demonstrated a higher proportion of time on educational URLs, with a lower ratio of time dedicated to educational web resources. Participants with self-report scores below-median contributed more of their online time to entertainment, social media, and educational websites. Participants enrolled in the intervention group dedicated an increased amount of time to educational web resources, peaking at nearly 35% of their total time online at the end of the first week. Although these findings are exploratory, this yet provides a basis for hypothesis forming: e.g. that learners overestimate their

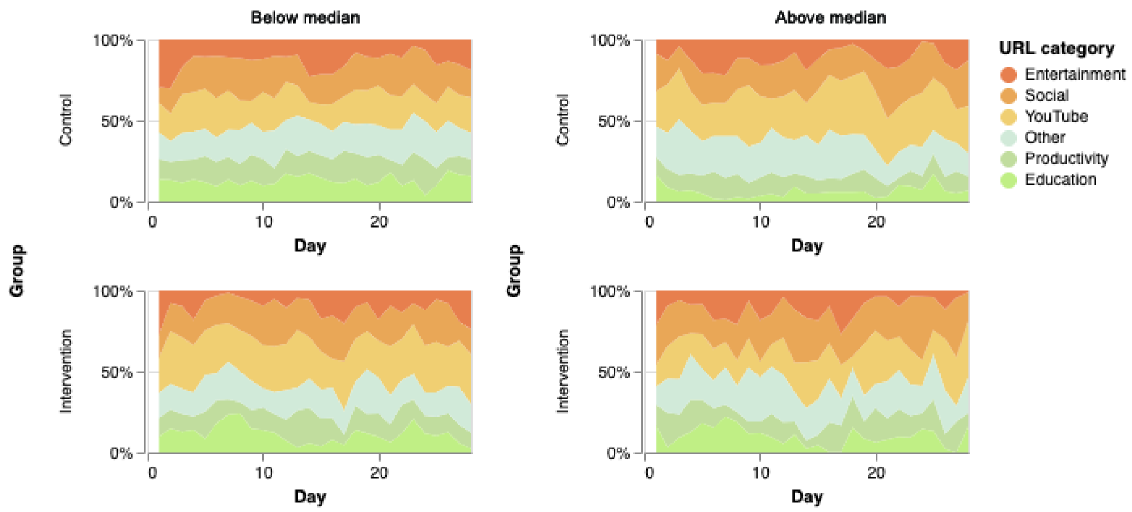


Figure 6.27 The role of the 'Agreeableness' personality trait in behavioural shifts in learners' self-regulation.

learning behaviour when responding to self-report questionnaires. Learners with below-median scores in conscientiousness are likely to benefit more from the intervention, as shown in Figure 6.26. In contrast, learners from the intervention group, regardless of their level of agreeableness, demonstrated a similar pattern in terms of the proportion of time committed to educational URLs, as can be noted from Figure 6.27.

The results of observed developmental and compensatory shifts between responses to self-report questionnaires and observed behaviour traces do not contradict the assumption that personality is an influencing factor in learners' response to the intervention. To conclude, the examination of learners' individual differences allows the limitations of learners' self-assessment of self-regulation to be revealed. Learners' responses reflect their self-perceived level of SRL, which is not necessarily a valid predictor of behaviour, and may not reflect learners' time commitment to different categories of web resources. It was shown in the visualisations provided that behaviour traces compliment the self-regulatory assessment, and the utilisation of both approaches (self-report and trace data) allows for distinctions to be made, and reveal the differential effect of learners' individual differences on responses to intervention provided.

7 | Discussion and Conclusion

This chapter summarises the results of the study, and discusses its findings in relation to theory, practice, and future research directions. This chapter also considers the limitations of the research. Overall, the results established the extent to which an online learner's potential lack of self-regulatory skills can be both compensated for and developed through the provision of adaptive online learning assistance. The following paragraphs further elaborate and summarise the findings. Next, the results of the study are linked to the theoretical foundations of this work. In the following sections, the limitations of the study, implications for practice, and future research directions are discussed. The last concluding section summaries the research findings and provides an overarching discussion of the study, contextualising the findings within the broader research field, and considering how this study might provide a jumping off point for future research.

Online learning has become an important aspect of contemporary life. For educational, personal, and occupational development, it is essential that learners are able to utilise learning opportunities offered online. The increasing popularity of delivering educational resources in digital settings has made educational opportunities more economical and more widely available. However, low completion rates, often due to a lack of support, are a common problem for many online learning environments. Self-regulation plays a key role in online learning environments, and, crucially, is a skill that can be acquired. To help learners maintain engagement with digital educational content, such as online training or courses, learners need to utilise their self-regulatory skills. Consequently, the purpose of this doctoral research project was to gain a better understanding of how the opportunities provided by online learning could be more effectively utilised by online learners.

To address the problem of the under-utilisation of opportunities offered by online learning, in this study self-regulated learning was conceptualised and operationalised. To lay the groundwork for this study, previous research relating to supporting self-regulated learning in online settings was reviewed. This informed the development of a system that promotes self-regulated learning: a virtual learning assistant which was utilised in this study as both an assessment and intervention tool to help online learners to remain engaged with their learning environments. The main assumptions were that self-regulation could be developed by exercising self-regulated learning, that events of procrastinatory behaviour could be identified from behaviour patterns based on trace data, and that failures of self-regulatory behaviour could be compensated for by using an adaptive assistance tool, which was designed to help learners to continue to participate in a given online course. Theoretical and practical advances in research on self-regulated learning were brought into play, informing the intervention design and selection of intervention components. These include (1) the conceptualisation of learners' self-regulation based on established theories (described in Chapter 2 and summarised in Section 2.4); (2) a review of state of the art SRL measurement options described in Section 3.3 and (3) intervention options that demonstrated their effectiveness in supporting learners' self-regulation in previously published studies (as described in Sections 4.1 and 4.2). Research on behaviour change was used to guide the intervention development and its practical realisation, as outlined in Section 4.3.

This research project aimed to answer two key questions: (1) to what extent the development of self-regulatory skills in learners can be facilitated by adaptive online learning assistance, and (2) to what extent a lack of self-regulatory skills in learners can be compensated for by providing adaptive assistance to help learners to persist in their online course participation. Additionally, the study aimed to examine the role of individual differences variables in developmental and compensatory shifts in learners' self-regulation. The overarching hypothesis aimed to discover whether online learners could be helped to improve their levels of self-regulation, exploring the ways in which developmental activities and compensatory strategies can be applied through environmental modifications in the form of providing adaptive assistance. In order to test this hypothesis, the Person – Task – Situation (PTS) framework (Beckmann and Goode, 2017) was applied, allowing the results of the intervention to be evaluated using the three-dimensional space of Person, Task and Situation, where 'Situation' was defined as the environment in which a learner performs a task. 'Task' was considered to be the combination of the learning problem and instructions given to solve the problem. 'Person' in this framework was considered as individual differences in cognitive and non-cognitive variables (Beckmann, 2010; Beckmann and Goode, 2017). The aim of adaptive assistance was to affect a person's level of self-regulation either through development, or by compensating for it, in cases when development was not possible.

In this study to assess learners' levels of self-regulatory skills and tracking learners' developmental and compensatory shifts in self-regulation in learning, both self-report and trace data measures were utilised. The analyses of self-report data revealed no statistically clear evidence for developmental changes in online learners as a result of the adaptive online learning assistant. However, behaviour trace data – especially in terms of changes in the frequency of identified lapses in self-regulatory behaviour over time – suggests effectiveness. Interestingly, these changes were not reflected in learners' self-perception about their levels of self-regulation in learning, as measured through a self-report questionnaire.

The potential compensatory effects of the intervention were examined at three levels: First, by looking at between-groups contrasts, second, by analysing behavioural response within the intervention group; and third, by analysing responses to individual components of the adaptive assistance intervention. Exploratory evaluations of trace data revealed that the compensatory function of the intervention might not work as intended, showing that participants' reliance on an external scaffold might not provide the support intended, as participants' time commitment to educational web resources surged in the first 10 days and declined thereafter, until the end of the third week of their respective online course. This was especially noticeable for learners with scores below median in the self-report overall baseline of self-regulation and conscientiousness. This is a somewhat counter-intuitive result pattern. Possible explanations may include a wearing off of an initial novelty effect (of the adaptive online assistant). Also, the often observed phenomenon of fading levels of commitment over time (Ho et al., 2014) might have also contributed to the overall pattern in the behaviour traces. An additional challenge is the fact that learners in the intervention group committed to longer learning sessions in the first two weeks per se, some learners spent up to five hours on educational URLs whilst time spent on educational URLs in the control group rarely exceeded three hours per day. Thus, it can be assumed that those apparently highly self-motivated learners in the intervention group were not in need of self-regulatory impulses as part of the intervention. This is especially relevant for self-paced MOOCs with their characteristically less strict timelines. Consequently, learners enrolled in the intervention group did not increase their learning time (further).

Learners in the intervention group spent overall less time online during the first three weeks, with a particularly low proportion of visiting entertainment websites during first two weeks. This behavioural pattern can be interpreted as an expression of a compensatory shift in behaviour towards higher levels of self-regulated learning. These effects, however, seem to have been short lived, as after the initial three-week period, learners' behaviour tended to match the behaviour demonstrated in the control group. The exploratory evaluation of proximal outcomes, such as web navigation activity in the 30 minutes following a recorded event of procrastinatory behaviour, revealed that providing adaptive assistance to online learners was associated with a change in observed behaviour in terms of increased time spent online. This behaviour was time-varied and reduced over time. It was statistically unclear if the intervention helped online learners to persist with their online course during this short period. However, participants' daily behaviour was, nonetheless, distinct between groups, which can be arguably attributed to the compensatory effect of adaptive assistance for the duration of up to three weeks. Nevertheless, it is believed that the adaptive assistance intervention can function as a useful supporting tool for some groups of online learners on short duration MOOCs and other brief online courses.

In sum, with the utilisation of PTS framework, this study demonstrated that targeted changes of situational components of an online learning environment, i.e. implementing impulses for developmental activities and compensatory strategies, can help online learners improve their levels of self-regulation and, therefore, increase their chances of performing the learning task more successfully. The potential effects of such interventions on learners' self-regulatory skills can be evaluated and measured through self-reports and the analysis of behavioural traces. Research on behaviour change underpinned the approach to engaging learners in developmental activities and in deploying compensatory strategies. Individual differences in learner characteristics were taken into account to explore how the effectiveness of the intervention can be maximised. The results of the study revealed that the adaptive assistance intervention did not result in a noticeable developmental shift in learners' self-regulation, as assessed by the self-report measures. However, participants assigned to the intervention group spent less time online per day in first three weeks of their exposure to the adaptive assistance, reducing their time commitment to entertainment websites during the first two weeks, and increasing their engagement with educational web resources during the first ten days. In short, the intervention seems to have led to a more efficient use of online time in terms of learning. In addition to these time-varying effects, compensatory shifts were determined by participants' individual differences variables.

7.1 Contributions to theory and methodology

The analyses conducted into developmental and compensatory effects of the adaptive assistance intervention contributes to the field of SRL theory in three key ways. First, it demonstrated the importance of utilising both self-report and behavioural traces to assess learners' SRL. Second, it showed the importance of the timing and content of feedback received by learners on their self-regulatory behaviour. Third, the design of the intervention was innovative, bridging behavioural, cognitive, and constructivist approaches to learning. This design enabled the importance of a multifaceted approach to supporting learners' self-regulation to be highlighted.

The first contribution of this study is in its demonstration of the importance of utilising both self-report and behavioural traces to assess learners' SRL. A data collection method should be informed by a theoretical and conceptual framework that reflects the study's approach to addressing a given research question. Research in self-regulation often relies on self-report data to ascertain information about developmental or intervention-related effects. The research presented here includes methods of obtaining behavioural trace data longitudinally. This decision was informed by the conceptual distinction between compensatory effects and developmental effects in self-regulation. By relying on one single form of data collection method, one could have either overclaimed or overlooked the effects of the self-regulation intervention (administered in the form of adaptive assistance).

The availability of large datasets associated with learners' outcomes and trajectories on online courses, utilising trace data has emerged as a fruitful stream of research in self-regulated learning (Panadero, Klug and Järvelä, 2016). Self-regulatory skills can be assessed using behaviour traces, which are processed through the application of a variety of methods, such as educational data mining (Biswas et al., 2018), in order to ascertain otherwise hidden patterns in online learners' behaviour. These hidden patterns may indicate self-regulation habits (Corno, 2011), different SRL profiles (Kim, Yoon, Jo and Branch, 2018), and the employment of self-regulated learning strategies (Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales and Munoz-Gama, 2018). This approach has also been adopted in more recent studies (Jansen et al., 2020; van Alten, Phielix, Janssen and Kester, 2020), which have utilised both trace data and learners' self-report SRL questionnaires to assess the effect of providing video interventions and prompts in supporting learners' self-regulation. This approach enables a fine grained assessment of learners' self-regulatory skills alongside any changes in response to the provided interventions. In addition, Moreno-Marcos et al. (2020) have utilised a similar approach, combining self-reporting and behaviour data to predict MOOC dropout rates. However, the application of trace data in their studies was limited to traces within course management systems.

Collecting event data during observations of learners' interactions with online environments and course content is an effective and universally applicable approach to collect informative data about learners' characteristics and their interactions with different tasks and environments yet it is minimally intrusive. The kinds of 'backend' measures and patterns extracted from the data equip researchers with insight into self-regulation, its complex components and developmental trajectories. For example, applying educational data mining methods to measure affect showed promise in a study concerning automatic affect detection (Baker, Ocumpaugh, Gowda, Kamarainen and Metcalf, 2014). Further, advances in stealth-assessment and research validated the stealth-assessment approach showed promise in the use of measurements based on trace data gleaned from participants playing digital games (Shute and Ventura, 2013; Ventura, Shute and Zhao, 2013). The present study has shown that behaviour traces to measure learners' self-regulation can be obtained not only within one platform (e.g. a single course measurement system, or a single gaming platform), but also in naturalistic settings, learners' web environments (where two or more distinct educational resources can be utilised), and can be combined with data regarding learners' self-regulation as assessed via conventional self-report measures.

For example, the results of the empirical part of the study showed that a small fraction of participants' categorised URLs accounted for nearly 80% of their total time online (study participants visited 17,064 URLs, but spent 78.2% of their total time online on just 273 URLs, which is about 1.6% of the total visited URLs, as described in detail in Section 6.3 on page 124). Further, learners spent nearly half their total time online on websites categorised as entertainment, social media, and YouTube (as illustrated in Figure 6.10 on page 129). Further, learners' time allocation was distinct, as shown in Figure 6.25 on page 153, according to their baseline self-report SRL scores. This web navigation behaviour demonstrated the potential availability of hidden opportunities and resources for learners' to invest in online learning.

The findings from the above example reinforce the assumption that, with the increasing number of opportunities offered online (outlined in Chapter 1), online learning environments are characterised by the prevalent role of potential distractions in learners' time allocation, such as entertainment and media platforms. In particular, learners' online environments are dominated by a limited number of resources, such as the video hosting website youtube.com, the social networking website facebook.com, and the web messaging app whatsapp.com (for more details see Table 6.9 (c) on page 123). These findings added new evidence to previously published research on learners' technology use and the role of distractions in the context of online learning (see, for example, Chen, Nath and Tang, 2020; Cheong, Shuter and Suwinyattichaiporn, 2016; Hood et al., 2015; Robal et al., 2018).

The approach to utilise both self-report and behavioural traces data allows data to be cross-validated across multiple measures (Cleary, Callan, Malatesta and Adams, 2015), leading to valid results. Using a real-time assessment based on trace data and validated using traditional assessment methods is particularly important to understanding the learning process in massive open online courses (Reich, 2015). Currently, cross-validation of self-reported and trace data is the most promising method of assessing self-regulated learning, as noted by Panadero et al. (2016).

The application of self-report and behavioural measures to assess learners SRL revealed that participants may not always be able to correctly estimate their levels of self-regulatory behaviour. Thus, it can be argued that learners often overestimate their levels of SRL. This finding is in line with previously published studies that stressed the importance of cross-validating self-report and behavioural measures to assess learners' self-regulation (Bernacki, Vosicka and Utz, 2020; Cleary et al., 2015). This finding resonates with the study conducted by Lust et al. (2013). The authors demonstrated that learners might utilise the support provided in ways that do not adequately correspond to changes in their environments:

> Hence, although all students regulated their tool-use and were thus aware of the cues in the learning environment, only a minority (3%) was able to regulate one's tool-use in line with the course' phases and hence with the changing requirements. Consequently, it seems that most students had erroneous conditional knowledge which caused them to regulate their tool-use wrongly. (Lust et al., 2013, p. 394)

The authors linked their findings to Winne's SRL model (1996), where students' conditional knowledge was found to be bi-faceted and consisting of 'objective' and 'subjective' facets, influencing students' regulative behaviour conjointly (Lust et al., 2013, p. 394). Thus, self-reported SRL measures may not correspond to expected self-regulatory behaviour due to false facets of learners' conditional knowledge. This is an important finding, as developing self-regulated learning requires an examination of initial levels of SRL in order to design and provide appropriate support (as discussed in Section 2.4). It confirms that using both approaches (self-report and behaviour measures) may help to eliminate the difficulty in identifying the right state to begin providing scaffolding support (as discussed in Section 2.1.1). As demonstrated and briefly discussed in Section 2.2, learners may overestimate their learning behaviour when responding to self-report questionnaires. Thus, using both self-report and behavioural measures should allow for the identification of a more precise starting point from which to provide SRL support.

The second contribution made by the results of the study to SRL theory is the demonstrated importance of the timing and content of feedback received by learners on their self-regulatory behaviour. The provision of the adaptive assistance intervention was guided by learners' behaviour, and the appearance of the intervention acted as feedback to learners on their behaviour. The importance of feedback was stressed in SRL models proposed by Butler and Winne (1995), Winne (1996), and Zimmerman (2000). The later was chosen as the most prominent model in terms of guiding the study (described in Section 2.4). In line with the Zimmerman's (2008) notion regarding the need for studies that track learners' adaptations based on personal feedback, the findings from the empirical part of this study highlighted specific nuances of timing and content options when providing feedback to learners.

The multidimensional approach to self-regulated learning proposed by Zimmerman (2000) can be utilised to explain differences in learners' behaviour. As shown in Section 6.4, learners' individual differences variables demonstrated a distinct response to the adaptive assistance provided. This observation contributes to SRL theory in the way that a multidimensional view on learners' self-regulation could be applied to learners' responses to feedback on their behaviour provided in the form of on-screen adaptive notifications. In addition, according to Zimmerman's model of SRL, learners seek positive feedback and encouragement throughout each developmental phase of SRL (as described in Section 2.3.1 and Zimmerman, 2000, p. 25-26). However, as was demonstrated in Section 6.3 on page 141, it was not clear if providing positive feedback resulted in a short-term effect on learners' behaviour (expressed in time spent on educational web resources after receiving notifications relating to their online course, following a 25-minute learning session).

Although it was unclear whether providing feedback (in the form of adaptive assistance) contributed to learners' SRL development, the observed results can be linked to one of the principles of learning, attributed to Vygotsky. This principle assumes that one step in learning represents a hundred steps in development (Zaretskii, 2016). In relation to the observed findings, this principle can be modified: several steps in observable behaviour may be required before it becomes possible to observe developmental changes. As in the case of Piaget's developmental stages (Piaget, 1952), Vygotsky' development for voluntary attention (Vygotsky, 1981a), and Zimmerman's (2000) SRL phases, SRL development occurs in several steps, as described in detail in Section 2.3. Thus, among the possible reasons as to why the developmental effect of the adaptive assistance intervention was not identified is the possibility that the intervention was delivered at an inappropriate time (i.e. during an inappropriate phase of SRL). Another possible explanation for the lack of strong evidence for developmental changes is the limited length of the intervention; for learners to work through each SRL phase may take longer than the period of one month.

Furthermore, learners' behaviour in response to feedback showed a reduction in the effectiveness of the intervention over time. This might indicate latent changes in learners' SRL phases. Although the SRL theories considered emphasised the positive role of feedback on learners' SRL development, it can be argued that, at certain SRL phases, more control of the stimulus is needed to be transferred to learners (e.g. frequency of the adaptive assistance intervention). This argument does not contradict the SRL models proposed by Winne (Butler and Winne, 1995; Winne, 1996) and Zimmerman (2000). However, this argument stresses the importance of taking into account the degree of autonomy transferred to learners at each phase of SRL development. As Vygotsky has noted, 'Since the laws of stimulus-response connections are the basis of natural behavioural laws, it is impossible to control a response before controlling the stimulus' (Vygotsky, 1981b, p. 175–176, as cited in Fox and Riconscente, 2008, p. 385). Hence, it is important to provide learners with ways of controlling stimuli effectively. The PTS framework (Beckmann and Goode, 2017) applied in this study may, then, be applied to enable the right balance over learners' autonomy in controlling stimuli to be found and, further, to fine-tune learner-task-environment interactions.

In addition, in this study, a side attempt was made to implement the MOST framework (Collins, 2018), alongside research on behaviour change (Michie et al., 2014; Michie et al., 2011) for designing intervention options for inclusion as components of the adaptive assistance. A series of micro-randomisations were implemented in order to evaluate the effect of providing versus not providing adaptive assistance within the intervention group. As noted, time is an important factor in learners' responses to interventions. These findings support the statement made by Almirall, Kasari, McCaffrey and Nahum-Shani (2018, p. 32):

> To guide the construction of adaptive interventions, theories of change should not only articulate the mechanisms underlying student learning outcomes, but also specify when or how often meaningful changes in these mechanisms (or intermediate outcomes) are expected to occur. The element of time has to be explicit enough in these theories in order to guide the development of interventions that modify the treatment over time.

The third theoretical contribution of the study is the attempt to bridge behavioural, cognitive, and constructivist approaches to learning (Section 4.4). The preparatory stage of the study demonstrated that research in the area of behavioural analysis could be utilised in the design of educational interventions to support self-regulated learning, and is, particularly, linked to the social-cognitive perspective of learners' self-regulation. The empirical part of the study revealed that this approach could be successfully implemented in practice in the form of adaptive assistance intervention. This is possible in part through existing overlaps between theoretical stances applied here. For example, Dinsmore, Alexander and Loughlin (2008) has suggested that some ideas in Bandura's works exerted ideas of neobehaviorism (p. 393). Further, a number of contemporary interventions that have implemented behavioural research have been rooted in Bandura's ideas of self-efficacy (Michie, West, Campbell, Brown and Gainforth, 2014, p. 329) and social cognitive (Michie et al., 2014, p. 359) theories. Therefore, the theoretical symbiosis manifested here might offer a framework for future studies when, for example, designing intervention options.

7.2 Limitations of the study

Limitations of the study conducted include the issue of participants' attrition for providing their responses to the post-intervention SRL questionnaire, as well as areas for further improvement that emerged in the research, including the data analysis strategy and the precision of the collected behavioural traces.

The problem of participants' attrition was indicated in the previous chapter (Sections 6.1 and 6.2). The analysis of the data collected (Section 6.1) revealed observable patterns in participants' responses to the post-intervention questionnaire. For instance, high attrition was observed among participants allocated to the control group with high baseline scores in self-report SRL. It can be argued that this pattern reinforces the definition of self-regulated learners made by Zimmerman (1989). According to this definition, learners who are self-regulated 'initiate and direct their own efforts to acquire knowledge and skill rather than relying on teachers, parents, or other agents of instruction' (1989, p. 329). Thus, this pattern can be explained by the assumption that learners with high initial scores in self-regulation are perhaps more likely to be aware of their weaknesses, and were, as a result, in search of an instrument that would more actively support their learning. Furthermore, the decision to not adopt the tool can even be considered, in itself, the application of a self-regulatory strategy, as was briefly discussed in Section 6.1.

In addition to the observed drop out from the mentioned above category of participants, the high attrition rate was also observed among other participants with rather diverse sets baseline scores in their self-report SRL levels (as demonstrated in Figure 6.1 on page 109). This includes learners with relatively low and intermediate scores in their self-report SRL. Increasing the sample size, however, would not have solved the attrition problem as such. In comparison to on-site laboratory experiments, studies conducted in naturalistic and online settings tend to be characterised by high attrition (Arechar, Gächter and Molleman, 2018; Hansen and Tummers, 2020; James, John and Moseley, 2017). It can be assumed that increasing the sample size would increase the absolute number of participants remaining, assuming that the proportion of participants who responded to the post-intervention questionnaire remains constant. A larger absolute number of remaining participants (complete cases), in turn, should result in more precise coefficient estimates when analysing results statistically. As mentioned above, this only applies in the case of a stable proportion of enrolled participants and those who remain in the study to provide post-intervention responses. However, it should be noted that, as shown in Section 6.1, participants with certain personality traits, such as being higher in openness to experience, were more likely to maintain their participation (Figure 6.2 on page 112). Therefore, recruiting a larger sample would likely result in a relatively higher number of participants, which would increase the likelihood of receiving more complete data. However, this larger sample would still be characterised by participants with certain levels of self-report individual difference variables (e.g. the high in openness to experience personality trait), in comparison to participants who do not respond to the post-intervention questionnaire. Therefore, it can be concluded that longitudinal studies involving online learners tend not to be representative of the population of online learners in general. The effectiveness of an online assistant for learners with certain levels of self-report individual differences variables (low in openness to experience personality trait) cannot be concluded.

A possible solution to the issue of participants' attrition is to improve the functionality of the tool in order to collect self-report data regarding learners' self-regulated learning. For example, in previously published studies, browser extensions were utilised to collect self-report data, along with behaviour traces regarding learners' interactions with learning content. Tools that include extensions to web browsers, such as nStudy (Perry and Winne, 2006; Winne, 2017b, 2019, also outlined in Section 4.1), were used to provide learners with the opportunity to take notes regarding the educational content provided in their web browser environments. Next, traces collected regarding learners' note-taking activity were analysed and linked to SRL theory. Zimmerman (2008, pp. 171-172) illustrates this process with the following example:

> For example, a high frequency of note-taking trace could mean that a student is not selective in recording information, instead being

> comprehensive. When additional measures, such as interviews, are used in conjunction with trace measures, more valid conclusions can be drawn. The development of high-tech study environments is yet in its infancy, but its potential for assisting students to use SRL strategies is impressive.

Thus, additional functionality to collect self-report data can be added to the virtual assistant utilised in this study. For example, functionality that allows for participants with in-browser pop-up messages to be questioned about their current motivations, emotions and rationales for certain behaviour, or offered the option to save notes, as in the case of work by Winne (2019) who tracked participants' note-taking with their extension to web browsers. This additional functionality may help to mitigate the issue of the high attrition rate when repeatedly completing self-report data. Furthermore, as longer questionnaires administered online tend to receive lower response rates in general (Galesic and Bosnjak, 2009), hence using shorter questionnaires may increase their response rates. However, this poses a risk of collecting self-report data with more inferior measurement qualities. This is another trade-off to be weighed up, and its usefulness depends on the research context and participants' individual differences variables.

Another possible solution to overcoming the effects of observed high attrition rate on the confidence into the accuracy of the identified effects might be in utilising a Bayesian approach instead of the classical frequentist approach. In research literature in social sciences and medical studies, the Bayesian statistical approach has become increasingly popular for testing research hypotheses (Kruschke, 2013; West, 2016). The Bayesian approach assumes the use of prior information and accumulates evidence regarding the effects of an intervention. It allows researchers to give more power to their results, based on the same sample size. For example, in one study (Chen and Fraser, 2017), the classical frequentist t-tests were compared with Bayes Factors to test research hypotheses. The results of this study yielded that the frequentist approach provided 80% power, in comparison to 92% power gleaned from the Bayesian approach, based on the same sample size. Chen and Fraser (2017) concluded that the Bayesian approach might allow experiments on smaller samples to be conducted, whilst maintaining acceptable levels of statistical power (Chen and Fraser, 2017, p. 441). Transferring this argument to the research carried out in this thesis, the application of the Bayesian approach might yet have a limitation. The study conducted was unique in terms of delivering the adaptive assistance intervention within the participants' web browsing environment, and there is no known prior research which reports the effects of a similar intervention on learners' SRL skill development. An approximate prior effect could potentially be estimated based on research which uses other types of intervention options. However, an accurate prior effect of the applied intervention cannot be provided. Therefore, the Bayesian approach was not applied in this study to analysing results.

Another possible solution to minimising the negative consequences of the study attrition on the research findings would be to utilise the 'Intention to treat' approach. Intention to treat is a strategy for the analysis of RCTs that compares participants in the conditions to which they were originally randomly allocated by including all randomised participants to the final evaluation and computing their group average scores for all missing cases (Hollis and Campbell, 1999, p. 670). The main principle of the intention to treat approach is that once a subject has been randomised, it should always be analysed (Gupta, 2011). The intention to treat approach allows the introduction of bias as a consequence of potentially selectively dropping participants from randomised (balanced) groups to be prevented (Kendall, 2003). However, in some cases, the application of the intention to treat approach does not guarantee the best possible options for analyses, as it increases the complexity of data analysis and increases the potential for errors (White, Carpenter and Horton, 2012). It is usually recommended that the intention to treat analysis is included at least as a part of sensitivity analysis (Thabane et al., 2013; White et al., 2012), which helps to improve the robustness of reported results. However, in cases where more participants have 'dropped out' than 'survived' to complete the post-intervention measures, as in the case of the conducted study, the intention to treat approach should be applied with extra care, as noted by Johnston and Guyatt (2016, p. 1200):

> Probably the best way of dealing with missing data is to begin by analyzing only those patients for whom one has complete data (called a complete case analysis). Investigators should then conduct $\geq$1

> sensitivity analysis employing different assumptions for the missing outcomes to assess the robustness of their results. This is true both for individual trials and for systematic reviews and meta-analyses of RCTs. In the absence of an explicit approach, clinicians should be wary of studies reporting so-called “intention-to-treat” analyses in the face of substantial missing outcome data (in the case the of dichotomous outcomes, particularly if there are more missing participant outcome data then there are outcome events).

Therefore, the negative consequence of applying the intention to threat approach is the possibility of increasing the likelihood of an extremely conservative estimate of its effectiveness, or the increased chance of overlooking the true effects of the intervention. This is particularly applicable to examining the role of individual differences variables in the responsiveness to interventions. In summary, to respond to the attrition problem, the results of this study were extensively analysed in Section 6.1 in terms of their generalisability to online learners' populations. Given that only about a third of participants provided responses to the self-report post-intervention questionnaire, a complete case analysis approach was chosen. Taking into account the explanatory nature of the conducted study, the analysis of complete cases can be considered a reasonable option, as noted by Armijo-Olivo, Warren and Magee (2009).

Another limitation of the study is the possibility of an issue with data quality. Data collection in naturalistic settings implies a number of risks for data quality outside the control of researchers (Arechar et al., 2018). For example, with the application of the extension to participants web browsers, there is a risk that several members of one household may have used the computer with the extension installed. The potential solution to mitigate this issue in future studies is to include a screening question to determine if any other person uses the computer on a regular basis. However, this will naturally limit the variability of potential participants and may result in the problem of ecological validity of received findings. This trade-off should be considered, and it depends on the research context. Given that during this study, there was no access to a large pool of participants, this question was not included in the list of questions for the initial screening of participants' suitability for this study.

7.3 Implications for practice

The main aim of the empirical part of this study was to evaluate the effectiveness of the adaptive assistance intervention delivered in the web browser environment, with the intention to improve learners' self-regulation. This aim was achieved by evaluating the developmental and compensatory effects of the intervention, and the role of learners' individual differences variables in response to the intervention, with particular attention to the practical implementation of the intervention in naturalistic settings.

Accordingly, the first important practical contribution made by the results is the demonstrated suitability of the developed tool for application in practice. This study has shown that a web application, in combination with extensions to web browsers, can be utilised as a data collection tool for measuring learners' self-regulation. This is especially relevant to online courses that rely heavily on external learning resources outside their learning management systems as part of their curriculum. This study has shown that learners who seek help to improve self-regulation are ready to share their data and utilise external tools to aid their learning environment. Further, this study reported crucial findings relating to participants' study attrition, which can be taken into account in experiments with similar designs in order to estimate response rate and sample size calculations.

The second practical contribution of the study is in its ability to measure learners' self-regulation beyond course platforms. It has shown the clear benefits of going beyond the boundaries of online learning platforms to find ways to obtain a better understanding of learners' self-regulation. The results of this study follow an emerging strand of researchers and practitioners who have attempted to intervene and collect data on learners' self-regulatory skills beyond the narrow scope of learning environments (see, for example, works of Chen et al., 2016; Sapunar-Opazo, Pérez-Álvarez, Maldonado-Mahauad, Alario-Hoyos and Pérez-Sanagustín, 2018). Adding to this new strand of research and practice, this study demonstrated that it is possible to measure learners' self-regulatory behaviour in learners' web environments. This enables a range of possible applications in practice, such as developing a measurement tool with a broader scope of application across different learning environments. The assessment of self-regulatory skills beyond learning management systems and course platforms could help to overcome the problem of assessing learners on MOOCs, which struggle to find and implement suitable assessment models (Joksimović et al., 2018). The current study is aligned with the third wave of research of measuring self-regulated learning, following using self-report data alone as the first wave, and only behavioural data as the second wave (Panadero et al., 2016). Research findings from this study and learners' behaviour patterns extracted from it, equip intervention designers – and, ultimately, course instructors – with insights into self-regulation and its complex nature. Thus, for the purpose of personalising learners' experiences in online learning environments, learners' levels of self-regulatory skills need to be assessed continuously and non-intrusively in order to not unduly disturb the learning tasks at hand. The non-intrusive assessment of learners' self-regulatory skills might provide useful insights into learning processes. First, by providing an initial measurement of an individual's levels of self-regulatory skills. Second, such assessments can show the dynamic nature of self-regulation, as levels can be measured throughout a course, and against different contexts and tasks. Therefore, data regarding learners' self-regulation obtained beyond the scope of learning management systems can be utilised as a part of a wider university or course platform learning assessment programs.

The third practical contribution made by this research relates to the importance of providing timely and individualised feedback for affecting learners' online behaviour. As was shown in previous studies, students in a modern higher education classroom often use their laptops for engaging in off-task activities (Kraushaar and Novak, 2010). Instructors are, therefore, presented with the challenge of managing the effects of online distraction on the learning process.

> The myriad approaches elucidated here strongly suggest that instructors are challenged by the demands of digital media and are in search of pedagogical approaches that not only manage learners' uses of media but also preserve and yet reconfigure their authority in the classroom. (Cheong et al., 2016, p. 284)

As providing individualised feedback to students on their digital media usage is often impractical in large classroom's settings McGloin, McGillicuddy and Christensen (2017) propose a way to mitigate this problem:

> However, by encouraging students to become more aware of their own usage, and to reflect on how it impacts their educational goals, instructors may be able to help lead their students toward better usage decisions. (McGloin et al., 2017, p. 260)

As it the results of the current study suggest (Section 6.3), learners spend a significant proportion of their time on web resources categorised as entertainment and social media. Therefore, the problem of learners' disengagement from learning content is not only related to learners being present physically in a classroom, but is also relevant to learners studying on their own schedule, with the flexibility provided by online learning. It seems that learners also spend a significant amount of time on off-task behaviour. Therefore, the proposed intervention and results indicate that providing feedback on learners' behaviour in the form of adaptive assistance may be an effective tool in supporting the instructors' role in a classroom. Thus, the function of tracking behaviour and initiating feedback should be augmented by the assistant. However, to make this intervention effective, instructors' involvement might be needed to specify a particular set of decision rules, triggering the intervention (as described in Section 4.5), such as the timing and frequency of the intervention in a particular learning context.

Furthermore, in this study, the application of several intervention options wrapped in the form of feedback on learners' behaviour and the application of the micro-randomised trial data structure (for more details, please refer to Section 6.3) to evaluate the intervention were used. As a result of this approach, this study has shown that providing learners with external feedback poses many opportunities to test hypotheses, such as those related to the role of learners' individual differences variables in response to the adaptive assistance intervention, the role of the timing of the intervention delivery, and the role of intervention options (its content). This finding is in line with the research of Greene and Azevedo (2007), who have argued that providing learners with feedback on their self-regulatory behaviour allows for many novel hypotheses to be tested, such as the role of environments in students' learning and how it might be built into their future learning in novel situations:

> By systematically varying the type of external feedback in an experimental design, researchers could answer these questions and perhaps tailor future external regulation interventions on the basis of these results, as well as craft hypermedia environments with the appropriate levels and kinds of feedback (Greene and Azevedo, 2007, p. 363)

Therefore, the problem of increased exposure to distractions (Robal et al., 2018), coupled with a relative lack of support (Reich and Ruipérez-Valiente, 2019) in the context of online learning, in part, can be addressed by providing feedback to learners. In this thesis, the resulting adaptive assistance component of the virtual assistant was evaluated in a study that incorporated a combination of behavioural trace data and self-report measures. Self-report questionnaires, web navigation behaviour traces, and learners' responses to the intervention provided were examined to identify developmental and compensatory shifts in learners' self-regulation. The role of learners' individual differences in cognitive and non-cognitive variables was examined in relation to observed shifts in learners' developmental and compensatory self-regulation. In addition, individual components of the intervention were explored for their compensatory effects at different levels of detail, based on their categorisation according to behaviour change techniques and their functions. In sum, to make an intervention with feedback on learners' behaviour effective in terms of developing learners' self-regulation, the intervention should focus on compensatory strategies (as described in Section 4.2). The effect of such an intervention should be measured using behavioural trace data. Using self-report measures alone risks missing opportunities to capture compensatory changes. This facet of the research design is crucial; capturing compensatory changes at the fine-grained level should help gather information to make adjustments to the intervention, enabling developmental effects at a later stage.

To conclude, data regarding learners' self-regulation obtained beyond the scope of learning management systems coupled with providing feedback to learners can be utilised as a part of a wider university or course platform learner-retention program. This could be integrated alongside email communications (Pardo, Han and Ellis, 2016), twitter bots (Bayne, 2015), and discussion forums (Zhang, Meng, Ordóñez de Pablos and Sun, 2019).

7.4 Implications for future research

This study has opened up several fruitful avenues of exploration for future research, including improvements in the assessment of learners' self-regulatory skills to adjust the provision of the intervention, the evaluation of different intervention components to optimise the intervention, and the examination of ethical risks that would emerge along the above mentioned paths.

First, the assessment of learners' self-regulatory skills could be improved through a number of promising research directions. This should allow the starting point (or baseline level) of self-regulatory skills to be more precisely established, indicating an intercept and a slope for the estimated effects of a self-regulatory intervention. Among the options to improve SRL assessment, the next steps can be considered: (a) non-intrusive assessment of each phase of SRL; (b) clustering of learners' web navigation behaviour beyond learning platforms according to their self-report SRL scores; (c) identify procrastinatory behaviour, based on frequently appearing sequential patterns. These steps will be further examined below:

a Future research may aim to investigate associations between patterns in observed learning behaviour and changes in learners' self-regulation in order to develop and evaluate an instrument that can measure phases of self-regulation in online learning non-intrusively. To achieve this aim, a reliable and valid self-reporting questionnaire, such as the Online Self-Regulated Learning Questionnaire (Barnard et al., 2009) utilised in this study, could be used for repeated longitudinal assessment. Such approach could be used to cross-validate continuous event data collected in the field, learners' characteristics, their self-reports and responses to interventions. To assess SRL phases, as indicated in Zimmerman's model of learners' self-regulation (Zimmerman, 2000 and described in Section 2.3.1), attributes from observed behaviour could be identified for each SRL phase. The collected event data could include behaviour observations, such as time spent engaging with online learning environments and external web resources. In addition to web navigation data, learners' responses to different notifications could be taken into account. It can be assumed that this information could be indicative of learners' cognitive and motivational states. For instance, learners' responses to content in a notification message might provide some insights in terms of what underpins a learners' momentary motivation to complete an indicated learning target (e.g. some learners may reply positively to monetary tokens, others might respond more positively to social cues). Whilst a series of notifications can constitute an intervention, each notification can be seen as an intervention on its own. For example, a notification explicitly encouraging a learner to set goals, or to employ certain strategies for self-regulated learning would count as an intervention to a particular SRL phase. Thus, responses to such notifications could be informative in terms of the assessment of SRL phases and their development over time. Thus, future studies could be focused on the following two points: developing an instrument to measure learners' use of each phase of SRL in online learning, such as goal setting and self-monitoring based on learners' behaviour; evaluating the predictive utility of the instrument to assess phases of self-regulation in online learning.

b Learners differ inter-individually in their SRL profiles. The application of the Online Self-Regulated Learning Questionnaire (Barnard et al., 2009) differentiates between five distinct self-regulated learning profiles of MOOC learners (Barnard-Brak et al., 2010a; Barnard-Brak et al., 2010b). In another study, four SRL profiles were identified (Dörrenbächer and Perels, 2016). The classification of learners according to their self-regulatory skills can be supplemented with trace data across different courses and learning platforms. For example, in previously published studies, the classifications of learners' SRL profiles were based on six most frequent interaction sequence patterns identified across a number of different MOOCs (Maldonado-Mahauad et al., 2018), and SRL attributes which were calculated through their expression as log variables from a course taught on the Moodle learning platform (Kim et al., 2018). However, these two studies utilised other instruments to assess learners' self-report levels of self-regulation, such as a SRL questionnaire constructed based on existing scales (which was validated by the authors as in the first study by Maldonado-Mahauad et al., 2018), and the Motivation for SRL Questionnaire (Pintrich et al., 2000), as in the case of the second study (Kim et al., 2018). Thus, in future studies, self-report data and behaviour traces in naturalistic settings (independent of a specific learning management system) could be used together to achieve a more precise identification of learners' SRL clusters, as in Zimmerman's (2000) model of SRL.

c The provision of support in online learning environments could be improved based on further studies that encompass behaviour traces, self-report data, and expert coding to identify the occurrence of uncontrolled failures of self-regulatory behaviour and the need for intervention. For example, sequential pattern mining methods, such as the pattern-growth algorithm PrefixSpan (Fournier-viger, Lin, Kiran, Koh and Thomas, 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 to predict future steps in learners' web navigation. Making use of both approaches (the identification of frequently appearing patterns of web navigation behaviour associated with procrastination and the prediction of web navigation behaviour) could enable the need for an intervention to be identified before the problematic behaviour even occurs.

A second fruitful direction for further research would be to optimise the content and delivery of the intervention. To optimise the adaptive assistance intervention and select the most effective intervention strategies, the individual components of the intervention could be evaluated in separate trials. A range of analytic procedures and research designs could be applied, including factorial and fractional factorial randomisation trials, sequential multiple assignment randomisation trials, and micro-randomisation trials. For example, emerging analytical approaches to evaluate data, resulting from micro-randomisation trials, allow within-individual correlations of responses and time-varying effects of an intervention to be accounted for. In addition, based on an evaluation of the interventions' attributes and learners' individual differences variables, the contents of the notification messages contained in an adaptive assistance intervention could be further personalised with the application of corpus linguistics, for example, by applying chat bots to generate individually tailored messages as intervention options to support learners' self-regulation.

The results of regression models fitted to the available data with fitted curves demonstrated in this study (Section 6.3) were exploratory and should be taken tentatively. Therefore, in further studies, these exploratory conclusions could be further evaluated through confirmatory tests. Although the use of polynomial curves in the present study did not reveal causality in differences between groups, it creates, nonetheless, a possible starting point for further investigation. Such further investigations could utilise response surface analysis methodology (He and Côté, 2019) and the application of non-parametric trajectories for time-varying effect modelling (Dziak, Li, Tan, Shiffman and Shiyko, 2015). Thus, a future study could use these, or indeed similar approaches, to select the most effective intervention options for a learning population of interest. It is especially relevant for situations in which taking into account learners' individual differences variables for providing personalised interventions is not possible or economically practical.

In this study, the series of intraindividual randomisations applied at each event of procrastinatory behaviour within the intervention group (Section 6.3) is, in principle, similar to the sequential randomised trial design for developing adaptive interventions in scaled online learning environments, such as MOOCs, as proposed by NeCamp, Gardner and Brooks (2019). In addition to adding an extra layer of support in reporting the results of the exploratory evaluation, the approach presented here can be applied to assess the proximal effects of the different content options of the adaptive assistance, in order to further optimise the intervention.

The methodological approach to evaluating the adaptive assistance model in this study kept questions surrounding the effectiveness of intervention components open for further investigation. It demonstrated that the intervention could be evaluated at a different level of detail, and that further advances in the methodologies for evaluating interventions could be applied to explore the effect of individual intervention components. Discussions in the same vein have appeared in research literature, where methodological approaches to constructing and evaluating optimised adaptive interventions have been discussed. Hedges (2018) has suggested, for instance, the need to identify the effective components of intervention bundles, as well as effective sequences of treatments in response to the challenges of adapting rigorous research designs to the increasing complexity of educational interventions and their mechanisms, by which these interventions make an impact:

> Education science needs MOST trials [Multiphase Optimization Strategy], SMART trials [Sequential Multiple Assignment Randomized Trials], the variety of conventional randomized trials, and strong quasi-experiments to build a foundation of usable knowledge in education. (Hedges, 2018, p. 17)

However, as was pointed out by Almirall et al. (2018) in response to Hedges' proposal, methodological work to support complex intervention regimens has only recently begun to emerge in educational research, and '[a] great deal of methodological work remains to be done' (Almirall et al., 2018, p. 27). Thus, further statistical instruments are needed in order to evaluate intervention options that are activated in response to learners' behaviour. For example, more work is required to robustly infer causality regarding the effectiveness of an intervention from a micro-randomised trial where the intervention is delivered not with a pre-specified time interval, but that is delivered based on learners' behaviour. This future research direction should allow the intervention to be optimised, enhancing the support of learners' self-regulation on online learning environments.

Finally, the prediction of web navigation behaviour, identification of self-regulatory patterns, and intervention delivery based on these two steps poses significant ethical risks; incorporating interventions into the learning process may not work as intended, and it may change learners' attitudes and behaviour in unintended ways, or the long-term effects might be different from the observed proximal outcomes. Interventions may be perceived as violating learners' personal autonomy (analogously to AI-powered personalisation in MOOC learning, as discussed by Yu, Miao, Leung and White, 2017). Therefore, the ethical risks of applying research on behavioural change, coupled with novel approaches in statistical learning, such as applying intransparently artificial intelligence in intervention design, require further in-depth ethical examination, which could provide another crucial avenue for future studies.

To summarise answers to research questions set in this study, the first research question of this study yielded a key research finding: the adaptive assistance provided by the virtual learning assistant did not result in noticeable general developmental shifts in learners' self-regulation, as assessed via conventional self-report measures. The main finding for the second research question indicated that learners allocated to the intervention group spent less time online per day during the first three weeks of their exposure to the adaptive assistance intervention, reduced their time commitment to entertainment websites during first two weeks, and increased their engagement with educational web resources during the first ten days. In short, they responded to the adaptive online assistant with more efficient learning behaviour. In response to the third research question, this study revealed differential effects of learners' individual differences variables on responses to intervention. Learners who were initially below the median of the evaluated sample in self-regulation and lower in consciousness seem to have benefitted more from the intervention during the first two weeks in terms of a demonstrated increase in their time spent on educational web resources. These findings also suggest that learners' self-perception, as obtained using self-report measures, is not necessarily reflected in their actual online behaviour. This discrepancy between behaviour and self-report data could, therefore, be interpreted as behaviour changes which mark the first step towards the development of self-regulatory skills.

7.5 Conclusion

In conclusion, the virtual assistant employed in this study offered a novel approach in terms of delivering adaptive support in online learning environments. To help current and prospective learners to utilise the opportunities provided by online learning, such as the development of 21st-century skills (e.g. complex problem solving, self-regulation), and to become successful lifelong, self-determined learners, the virtual assistant introduced in this research allowed learners' self-regulation to be assessed in settings resembling their daily routines, using both self-report measures and behaviour traces. This allowed the proximal outcomes of the intervention to be examined at different levels of detail: between groups, within the intervention group, and at the level of individual components of the adaptive assistance intervention grouped by their attributes. The main contribution of this work is in its novel evaluation of the development and compensatory effects of providing adaptive assistance, and the role of individual differences variables in observed changes. This thesis, further, demonstrates the rich possibilities in designing educational interventions utilising advances in behaviour, cognitive, and constructivist approaches to learning.

This thesis has added to the evidence for the multifarious capacity of online learning assistants to be used as tools for data collection, assessment, and as intervention instruments to support online learners. This thesis contributes to the theory of self-regulated learning through its demonstration of the compensatory function of feedback in the form of adaptive assistance and its contribution to learners' behaviour change. Further, it reveals that learners' may not be able to adequately estimate their own levels of self-regulation and, therefore, that the assessment of learners' self-regulatory skills should include both self-report and behaviour traces data. The results of this study highlighted the importance of learners' individual differences variables in providing a response to interventions aimed to support learners' self-regulation.

To sum up, the results of this work 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 their online learners.

Considering the findings of this study, course designers may want to include behaviour measurements in addition to self-report data on learners' SRL in order to estimate more precise SRL levels, and to provide to learners with self-regulatory support based on this estimation. How learners naturally use their web environments, what additional learning resources they might access, how these resources can help them to navigate their learning path are all crucial considerations, as this study has made clear. Course designers can utilise these insights to adjust their course curriculum, chose practices applied by successful learners and distribute them to other course participants. As shown by the possibilities of the learning assistant used here, tracking learners' web navigation behaviour and their responses to the adaptive assistance intervention makes a key step toward in our ability to measure learners' self-regulation beyond course platforms. Therefore, course platforms could apply a similar approach to delivering SRL support to their learners beyond their learning environments, based on learners' individual differences variables. In future studies, the role of learners' individual differences variables should be emphasised in providing self-regulatory support in online learning environments, reflecting the dynamic and varied nature of the learning profile of the individual. As this study has demonstrated, one size does not fit all.

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A | Online Self-Regulated Learning Questionnaire

Online Self-Regulated Learning Questionnaire extracted from Barnard et al., 2009.

Item	Subscale
1. I set standards for my assignments in online courses. 2. I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the semester). 3. I keep a high standard for my learning in my online courses. 4. I set goals to help me manage studying time for my online courses. 5. I don't compromise the quality of my work because it is online.	Goal setting
6. I choose the location where I study to avoid too much distraction. 7. I find a comfortable place to study. 8. I know where I can study most efficiently for online courses. 9. I choose a time with few distractions for studying for my online courses.	Environment structuring
10. I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom. 11. I read aloud instructional materials posted online to fight against distractions. 12. I prepare my questions before joining in the chat room and discussion. 13. I work extra problems in my online courses in addition to the assigned ones to master the course content.	Task strategies
14. I allocate extra studying time for my online courses because I know it is time-demanding. 15. I try to schedule the same time everyday or every week to study for my online courses, and I observe the schedule. 16. Although we don't have to attend daily classes, I still try to distribute my studying time evenly across days.	Time management
17. I find someone who is knowledgeable in course content so that I can consult with him or her when I need help. 18. I share my problems with my classmates online so we know what we are struggling with and how to solve our problems. 19. If needed, I try to meet my classmates face-to-face. 20. I am persistent in getting help from the instructor through e-mail.	Help seeking
21. I summarize my learning in online courses to examine my understanding of what I have learned. 22. I ask myself a lot of questions about the course material when studying for an online course. 23. I communicate with my classmates to find out how I am doing in my online classes. 24. I communicate with my classmates to find out what I am learning that is different from what they are learning.	Self evaluation

B | International Personality Item Pool Questionnaire

20-Item Mini-IPIP (International Personality Item Pool) questionnaire with Five-Factor Model measure extracted from Donnellan et al., 2006.

Item	Factor	Text
1	Extraversion	I am the life of the party.
2	Agreeableness	I sympathize with others' feelings
3	Conscientiousness	I get chores done right away.
4	Neuroticism	I have frequent mood swings.
5	Openness	I have a vivid imagination.
6	Extraversion	I don't talk a lot. (R)
7	Agreeableness	I am not interested in other people's problems. (R)
8	Conscientiousness	I often forget to put things back in their proper place. (R)
9	Neuroticism	I am relaxed most of the time. (R)
10	Openness	I am not interested in abstract ideas. (R)
11	Extraversion	I talk to a lot of different people at parties.
12	Agreeableness	I feel others' emotions.
13	Conscientiousness	I like order.
14	Neuroticism	I get upset easily.
15	Openness	I gave difficulty understanding abstract ideas. (R)
16	Extraversion	I keep in the background. (R)
17	Agreeableness	I am not really interested in others. (R)
18	Conscientiousness	I make a mess of things. (R)
19	Neuroticism	I seldom feel blue. (R)
20	Openness	I do not have a good imagination. (R)

(R) = Reverse Scored Item

C | Participant Information Sheet

Shaped by the past, creating the future

Durham University
School of Education

Participant Information Sheet

Title: Assessment, development and compensation of self-regulation in online learning environments.

You are invited to take part in a research study on the evaluation of assessment, development and compensation of self-regulation in online learning environments. Please read this form carefully and feel free to ask any questions you may have before agreeing to take part in the study.

This study is conducted by Eduard Pogorskiy as part of his doctoral research project 'Assessment, development and compensation of self-regulation in online learning environments' at Durham University.

This research project is supervised by Jens Beckmann at the School of Education at Durham University.

The purpose of this study is to gain a better understanding of how the opportunities provided by online learning can be more effectively utilised by online learners.

If you agree to participate in this study, you will be asked to install the extension 'do useful' to your browser, create an account on the website www.douseful.com and login to your account. During registration, you will be asked to provide a username and your login details, to create your password, to read and declare your agreement to the terms and conditions of using the website www.douseful.com and the extension to the browser 'do useful', its privacy policy, the participant information sheet and the declaration of informed consent.

If you login to the website or install the extension to your browser, we will then collect certain information that is necessary in order to provide you with feedback. This content will be determined by you, but may include: your responses to questionnaires (Online Self-Regulated Learning Questionnaire and International Personality Item Pool questionnaire), your responses to pop-up notifications, list of domains that you visit, e.g. facebook.com, Instagram.com, mit.edu (without detailing the full URL of the pages), the date of your visit and time spent on those domains. All of your data will be assigned to automatically generated unidentifiable usernames such as '04ab7c4c-852f-4cad-9781-5a384734r191' or '9a7d5e23-771b-4ea3-94d0-7e9e45191d79' which will be used for data analysis and research purposes later in the study.

The information you submit to the website may be stored and used for academic and non-commercial purposes, and may also be disclosed to third parties, for example (but not limited to) other research institutions. Any disclosure will be in a strictly anonymous format to ensure that the information can never be used to identify you or any other individual user.

You are free to decide whether or not to participate. If you choose to participate, you are free to withdraw by sending an enquiry to Eduard Pogorskiy via email using the address eduard.pogorskiy@durham.ac.uk at any time without any negative consequences to you.

All responses given and data collected will be kept confidential. The records of this study will be kept secure and private. All files containing any information provided will be password protected. In any future published research reports, there will be no identifiable information included. There will be no way to connect your name to your responses at any time during or after the study in any report or publication resulting from this research.

If you have any questions, requests or concerns regarding this research, please contact Eduard Pogorskiy via email at eduard.pogorskiy@durham.ac.uk.

This study has been reviewed and approved by the School of Education Ethics Sub-Committee at Durham University (date of approval: 17/01/2019).

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D | Declaration of Informed Consent

Durham University
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Shaped by the past, creating the future

Declaration of Informed Consent

- I agree to participate in the study titled 'Development and compensation of self-regulation in online learning environments', the purpose of which is to gain a better understanding of how the opportunities provided by online learning can be more effectively utilised by online learners.
- I have read the participant information sheet and I understand the information provided.
- I have been informed that I may decline to answer any questions or withdraw from the study without penalty of any kind.
- I have been informed that all of my responses will be kept confidential and secure, and that I will not be identified in any report or other publication resulting from this research.
- I have been informed that the investigator will answer any questions regarding the study and its procedures. Eduard Pogorskiy, School of Education, Durham University can be contacted via email: eduard.pogorskiy@durham.ac.uk.
- I can print a copy of this form for my records.

Any concerns about this study should be addressed to the School of Education Ethics Sub-Committee, Durham University via email to ed.ethics@durham.ac.uk.

By registering an account on the website www.douseful.com or installing the extension 'do–useful' to your web browser you accept the terms and conditions described in the Participant Information Sheet and the Declaration of Informed Consent.

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E | Supplementary Visualisations

Self-report measures

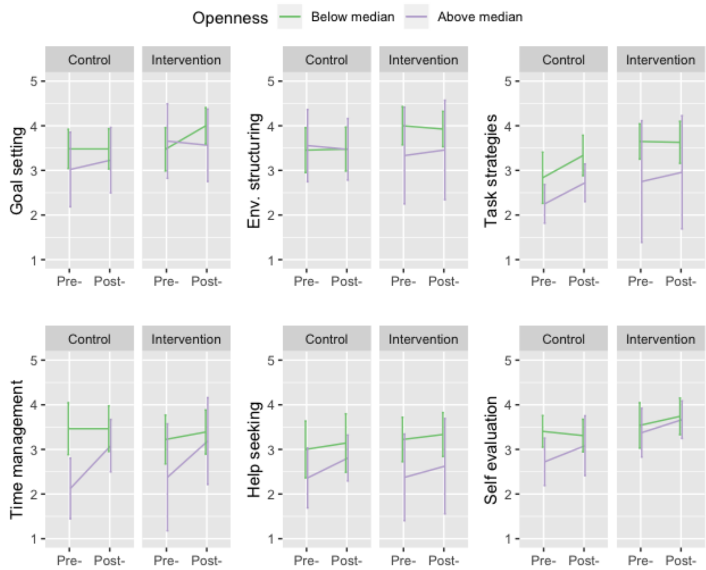

Figure E.1 The role of the ‘Openness’ personality trait in developmental shifts in learners’ self-regulation.

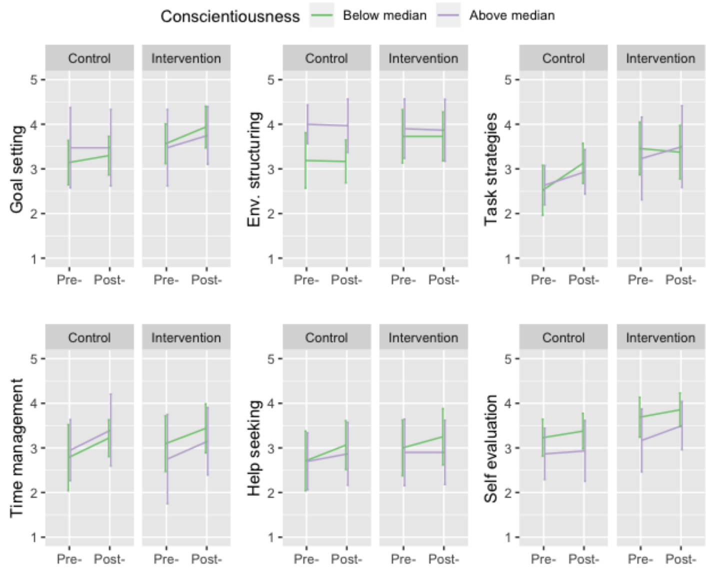

Figure E.2 The role of the 'Conscientiousness' personality trait in developmental shifts in learners' self-regulation.

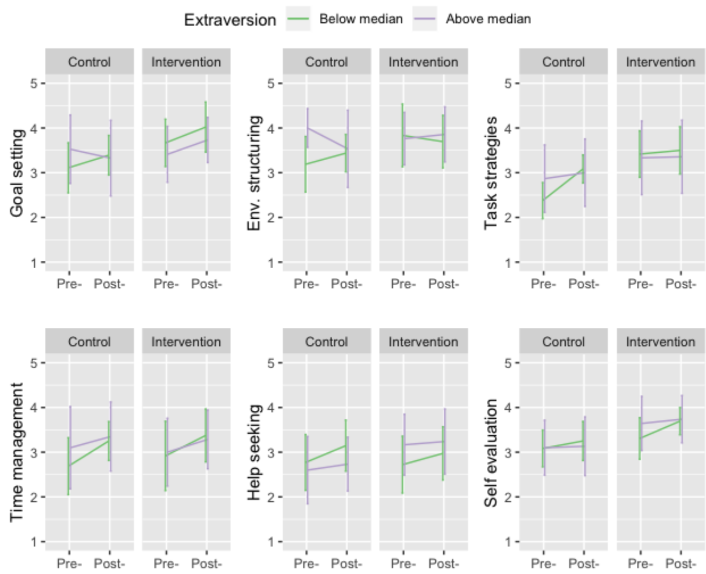

Figure E.3 The role of the 'Extraversion' personality trait in developmental shifts in learners' self-regulation.

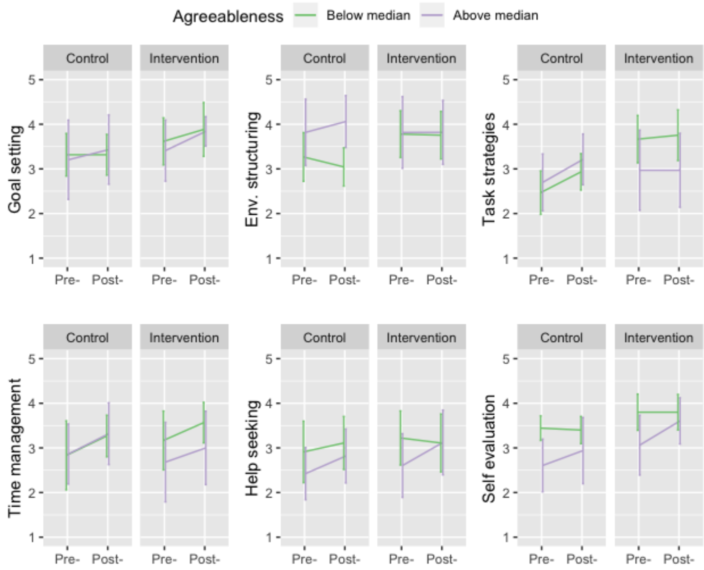

Figure E.4 The role of the ‘Agreeableness’ personality trait in developmental shifts in learners’ self-regulation.

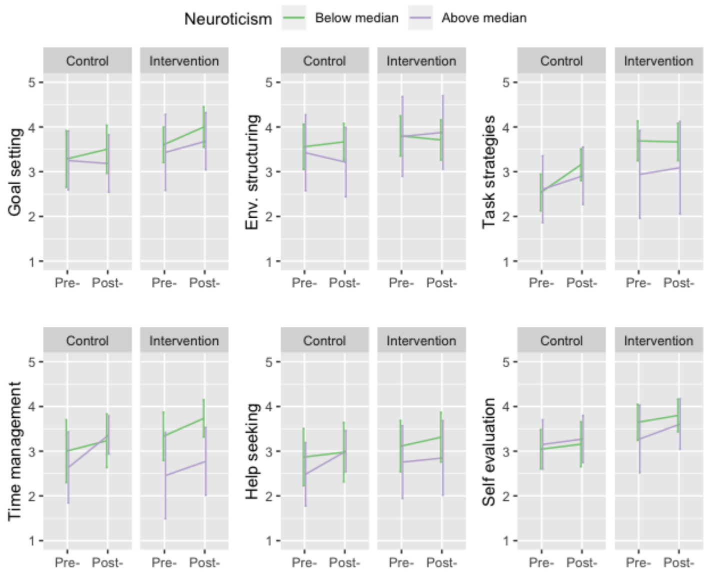

Figure E.5 The role of the ‘Neuroticism’ personality trait in developmental shifts in learners’ self-regulation.

Behavioural measures

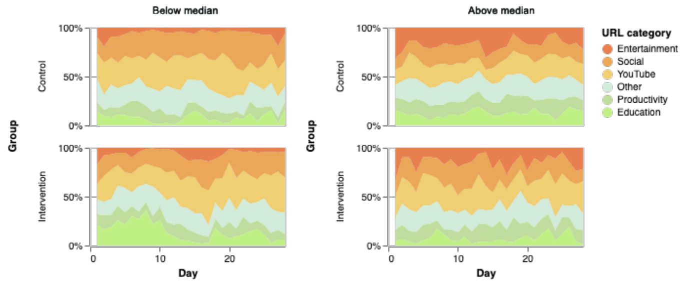

Figure E.6 The role of pre-intervention differences in overall self-reported level of self-regulation in behavioural shifts in learners' self-regulation.

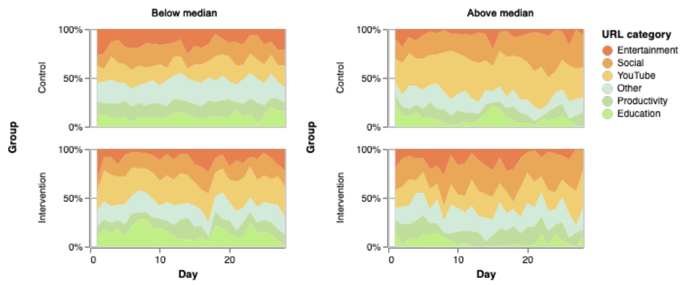

Figure E.7 The role of the 'Openness' personality trait in behavioural shifts in learners' self-regulation.

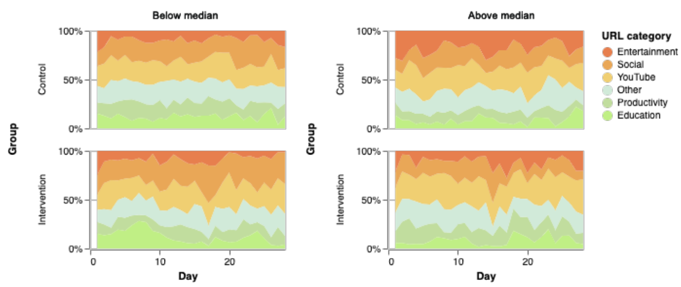

Figure E.8 The role of the 'Conscientiousness' personality trait in behavioural shifts in learners' self-regulation.

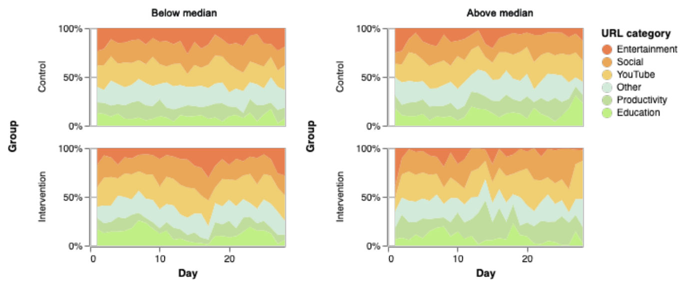

Figure E.9 The role of the ‘Extraversion’ personality trait in behavioural shifts in learners’ self-regulation.

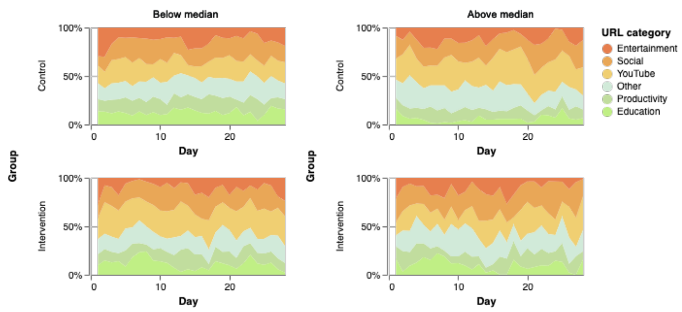

Figure E.10 The role of the ‘Agreeableness’ personality trait in behavioural shifts in learners’ self-regulation.

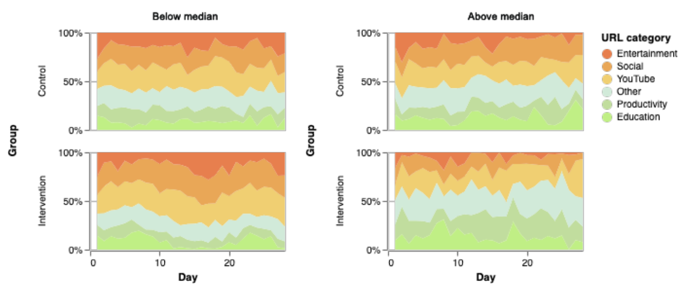

Figure E.11 The role of the ‘Neuroticism’ personality trait in behavioural shifts in learners’ self-regulation.