

MARILI RÕÕM

Multiple approaches to learners' success and
factors affecting it in computer programming
MOOCs



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To my family and friends

ABSTRACT

Technology affects all areas of life. Using and creating technology requires new knowledge and skills. One of these skills is computer programming (CP) and people with CP skills are increasingly needed. To acquire new knowledge and skills, lifelong learning has become a part of everyday life. One way to participate in lifelong learning is to learn in Massive Open Online Courses (MOOCs) as these courses provide access to quality education for a wide range of people. However, researchers have raised a question of how effective MOOCs are in terms of learners' success, as the number of completers is low in these courses. Although success is primarily linked with course completion, there are those who believe that in MOOCs it is more accurate to look at learners' success based on their intentions for the course. To understand learners' success, it is important to study the factors affecting it in association with both approaches to success.

The aim of this thesis was to determine which and how different factors affect learners' success in CP MOOCs. Quantitative dominant mixed methods research was used. This study was based on the expectancy-value theory as the characteristics of MOOCs and the participants of the MOOCs can be described through this theory. The focus was on three CP MOOCs organised by the research group of the Institute of Computer Science of the University of Tartu: "About Programming", "Introduction to Programming 1" and "Introduction to Programming 2". Quantitative data were collected with pre- and post-questionnaires, from the Moodle learning management system and from the Study Information System. Learning diaries were used to collect qualitative data.

The study attempted to determine which of the factors that, based on the expectancy-value theory, have influenced the expectancies and value (such as learners' background data and previous experience) have an effect on learners' success. Positive (motivation to enrol) and negative (learners' use of time) aspects of value were considered as the second type of factors. The last type of factors was related to the aspects influenced by expectancies and value (engagement, choices regarding MOOC activities, performance). Learners' background data, previous experience, motivation to enrol and engagement were studied in relation to learners' success, defined in terms of their intentions for the courses. This approach to success means that learners who completed as many or more mandatory activities during the course than they intended were considered successful. The impact of other factors was investigated based on course completion. In this approach learners are considered successful if they complete all mandatory activities.

The results showed that learners' success based on their intentions was affected by learners' education level, previous experience with course topic and online courses, usefulness related to certification as the only motivation factor, and visiting links to external materials as the only engagement factor. Regarding course completion, the periods of the highest dropout rates were at the beginning of the

course and also towards the end of the course, if the course included a project. Course completion was affected by learners' use of time, their choices regarding MOOC activities, and performance before dropping out. Based on these results and the results of previous research a model is presented to show the factors affecting learners' success according to the two approaches.

The results of this thesis can be useful for understanding the different approaches to learners' success in MOOCs and the factors influencing success. An overview of diverse factors that may affect the success of learners is given and a model is presented that summarises the results of this thesis and theoretical background based on quantitative and qualitative evidence. This study extends the research of learners' success, especially when success is based on learners' intentions. The results may be useful for course organisers to better understand course participants' behaviour and support needs in relation to success and provide input to make MOOCs more cost-effective.

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LIST OF ABBREVIATIONS

AP	MOOC “About Programming”
AP18	MOOC “About Programming” that was organised in the autumn of 2018
AP19	MOOC “About Programming” that was organised in the spring of 2019
C	Completer
CHAID	Chi-Squared Automatic Interaction Detection
CP	Computer programming
FIEM	Factors Influencing Enrolment in MOOC scale
IP1	MOOC “Introduction to Programming I”
IP2	MOOC “Introduction to Programming II”
MOOC	Massive open online course
NOC	Non-completer
STEM	Science, technology, engineering and mathematics

LIST OF ORIGINAL PUBLICATIONS

Publications included in the thesis

- I **Rõõm, M.**, Lepp, M., & Luik, P. (2021). Dropout time and learners' performance in computer programming MOOCs. *Education Sciences* 11, 11(10), 643. <https://doi.org/10.3390/educsci11100643>
- II **Rõõm, M.**, Luik, P., & Lepp, M. (2023) Learner success and the factors influencing it in computer programming MOOC. *Education and Information Technologies*, 28, 8645-8663. <https://doi.org/10.1007/s10639-022-11535-1>
- III **Rõõm, M.**, Luik, P., & Lepp, M. (2020) Learners' use of time in MOOCs about programming. In *EDULEARN20 Proceedings* (pp. 4380-4387). IATED. <https://doi.org/10.21125/edulearn.2020.1162>
- IV **Rõõm, M.**, Luik, P., & Lepp, M. (2020) Learners' Sequence of the Course Activities During Computer Programming MOOC. In *European Conference on e-Learning* (pp. 452-459). Academic Conferences International Limited. <https://doi.org/10.34190/EEL.20.032>

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Publications I-IV: formulating the research questions, data analysis, literature review, writing the paper as the main author.

Other published work of the author

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1. INTRODUCTION

1.1. Research problem

In today's society, technology affects all areas of life, and the creation and adoption of new technologies require people to develop new knowledge and skills. Programming has become one of the essential skills and is considered a core competency for jobs in the current century (Bey et al., 2018). People with programming skills are increasingly needed (OECD, 2022). Therefore, there has been an interest in teaching programming at all levels of education (Moresi et al., 2021), and the desire to learn to program has grown in recent years (Dolgopolas et al., 2018). However, programming is a complex subject to teach (Luxton-Reilly et al., 2018) and to learn (Babori, 2022; Gomes & Mendes, 2014). Learning programming is especially problematic for beginners (Babori, 2022). Therefore, the dropout rates in programming courses are high (Babori, 2022; Gomes & Mendes, 2014). Along with beginners, experienced programmers also need to upgrade their programming skills constantly, and therefore, they must participate in lifelong learning (Schumm et al., 2012).

In addition to programmers, lifelong learning has become a mandatory part of every person's life, stemming from people's interests and personal and professional needs (Kaplan, 2016) and requiring self-motivation and self-organisation (Farrow, 2018) to develop their skills and talents during the ongoing process (Kaplan, 2016). Lifelong learning is moving in a direction where the focus is on developing skills, not acquiring qualifications (Farrow, 2018), enabling the removal of restrictions between people, such as age, education level and socioeconomic status, and creating equal opportunities for everyone (Kaplan, 2016). Universities are seen to have an essential role in providing education as a part of lifelong learning (Stohr & Farnevik, 2020), and universities need to reach a broader range of people with their lifelong learning programs (Saridaki & Papavassiliou-Alexiou, 2022).

Massive Open Online Courses (MOOCs) have been seen as a bridge between universities and learners who want to obtain new skills (Semenescu et al., 2020) and as a possible lifelong learning solution to keep up with the rapidly growing need for education in general (Buhl & Andreasen, 2018) and also to deal with the large number of people who want to learn programming (Luik & Lepp, 2021; Moresi et al., 2021). There is no standard definition of MOOC, but MOOC is considered *Massive* as there is no limit to the number of participants; *Open* as anyone can register; *Online* as it is web-based; and *Course* as it is developed for online learning (Goopio & Cheung, 2020). MOOCs enable participants with different backgrounds (Littlejohn et al., 2016; Moreno-Marcos et al., 2020) and experiences (Jansen et al., 2020; Littlejohn et al., 2016) to learn from anywhere (Gitinabard et al., 2018; Littlejohn et al., 2016; Moreno-Marcos et al., 2020) at their own pace (Jansen et al., 2020; Moreno-Marcos et al., 2020) and at a time of

their choosing (Jansen et al., 2020). MOOCs are not accredited (de Freitas et al., 2015; Janakiraman et al., 2018), have no prerequisites (Janakiraman et al., 2018) or requirements for qualification (Semenescu et al., 2020), and no fees (Gitinabard et al., 2018; Janakiraman et al., 2018; Li et al., 2021). MOOCs can provide an opportunity to reach a wide range of people with high-quality learning resources (de Freitas et al., 2015) needed for personal and professional development (Aydin & Yazici, 2020). The specific characteristics of MOOCs and the nature of the learners who study in MOOCs are related to the expectancy-value theory (Lee & Song, 2022). The expectancy-value theory (Eccles et al., 1983) is important in understanding learners' academic performance, especially in the STEM (science, technology, engineering, and math) field (Goegan et al., 2021) and it enables to study participants' choices while attending MOOCs and their desire to continue learning in MOOCs regardless of what obstacles they face (Lee & Song, 2022). Therefore, the expectancy-value theory is the basis of this thesis.

MOOCs have created new educational opportunities, but there has also been a question of how effective MOOCs are in terms of learning (Romero-Rodríguez et al., 2020; Sabanwar et al., 2022), as researchers have cited the low number of MOOC completers as a significant concern (Goopio & Cheung, 2020; Khan et al., 2021; Sabanwar et al., 2022; Vitiello et al., 2018). Most enrollees in MOOCs cannot complete these courses (Moreno-Marcos et al., 2020) as several studies have shown the completion rate being less than 10% (Chen et al., 2020a; Goopio & Cheung, 2020; Sabanwar et al., 2022). Previous research (de Freitas et al., 2015; Ihantola et al., 2020; Reparaz et al., 2020; Zhang et al., 2021) has shown contradictory results on the periods when learners are most likely to leave a course, and therefore, this topic needs further study as researching the dropout time provides course organisers with information (Ihantola et al., 2020) on the points in time when learners need the most support to continue learning. In this thesis, dropout time is determined similarly to Ihantola et al. (2020) by the last week of engagement.

Course completion has been the primary basis for reviewing learners' success in MOOCs (Avello et al., 2020; Padilla Rodriguez, 2020). This is also reflected in this thesis, as the theoretical background focuses mainly on success in relation to dropout. However, there is another approach to learners' success, and it is based on course participants' intentions regarding MOOCs. According to this, learners are successful if they complete as much of the course as they initially planned (Henderikx et al., 2017). Extending the existing research with different aspects of learners' success with MOOCs is essential. On the one hand, the dropout rate of a MOOC is a significant success measure of the course, as only these participants who stay on the course can benefit educationally from the planned learning experience (Hone & El Said, 2016). On the other hand, focusing only on dropout rates is insufficient to understand the success of MOOCs (Avello et al., 2020; Chaker & Bachelet, 2020) as learners have different intentions when they sign up for a MOOC (Semenescu et al., 2020), and these may not coincide with the ideas of

course organisers in terms of course completion (Henderikx et al., 2017; Stracke, 2017). In this thesis, learners' success is viewed firstly via course completion, where learners who meet the criteria for completing the course are considered successful. Secondly, as suggested by Henderikx et al. (2017), learners' success is studied as the difference between learners' intention for the course and actual performance. In this case, a successful learner completes as many or more course activities as initially intended.

To understand learners' success in MOOCs, researchers have been interested in the factors affecting it. The fact that dropout has been the focal point of defining learners' success has resulted in research being geared towards the success factors that are related to dropout (Aydin & Yazici, 2020; Eriksson et al., 2017; Rawat et al., 2021; Shapiro et al., 2017). It raises the question of which of the factors that affect dropping out of MOOCs also affect learners' success when success is examined in terms of learners' intentions for the MOOCs, and it needs further study. Moreover, the research on dropout reasons is not complete as the reasons why course participants leave MOOCs in such large numbers are unclear (Canchola González & Glasserman-Morales, 2020), and especially the factors that are barriers to success in MOOCs need further investigation (Chansanam et al., 2021). One of the leading influencers of dropout has been a lack of time (Aydin & Yazici, 2020; Eriksson et al., 2017; Semenescu et al., 2020; Shapiro et al., 2017). In an educational environment, what is important is not the amount of available time but the capability to use the time by prioritising and organising the activities (Sainz et al., 2019). Therefore, additional research is needed on how learners use their time while studying on MOOCs and which factors affect their use of time. Participants have also pointed out course-related factors, like the perception of the course content and design, that have moved them to leave MOOCs (Eriksson et al., 2017). In an online learning environment, learners are expected to autonomously control their learning process (Onah et al., 2021), but not all of them can do this effectively (Albelbisi, 2019). Therefore, learners behave differently with course resources (Maya-Jariego et al., 2020). To understand which resources are used and to help to support participants during the course, information is needed on how and why learners use the resources. In summary, this thesis could contribute to expanding upon learners' success in MOOCs and a deeper understanding of approaches to success and the factors influencing these.

1.2. The focus of the research

This thesis aims to determine which and how different factors affect learners' success in computer programming (CP) MOOCs.

The following research questions are addressed in this thesis:

- RQ1: During which periods do learners drop out of CP MOOCs the most?

- RQ2: How do dropouts perform before the end of the dropout week in terms of successful completion of mandatory activities in CP MOOCs?
Research questions 1 and 2 are addressed in Publication I.
- RQ3: Which factors affect learners' success based on their intentions in CP MOOC?
Research question 3 is addressed in Publication II.
- RQ4: How do learners perceive their usage of time and the factors affecting it in a CP MOOC?
Research question 4 is addressed in Publication III.
- RQ5: How do learners describe their sequence of completing the course activities and their justifications for this preference in CP MOOCs?
Research question 5 is addressed in Publication IV.

2. THEORETICAL BACKGROUND

This chapter provides an overview of the theoretical outline of the thesis. First, different approaches to conceptualising learners' success in MOOCs are discussed, followed by an overview of the periods when participants drop out of MOOCs the most. The last section dissects various factors that influence learners' success in MOOCs.

2.1. Success in MOOCs

In MOOCs, success is not a fixed phenomenon and can be different for course organisers and learners in these courses. The expectancy-value theory helps to understand learners' success in large courses (Goegan et al., 2021). This theory focuses on two aspects. First, expectancy indicates people's beliefs about how well they will perform in a task (Eccles & Wigfield, 2020). Second, the value assigned to a task shows the extent to which the task helps fulfil needs and goals and corresponds to personal values (Eccles et al., 1983), i.e. the reasons why tasks are taken. Expectancies and value affect learners' persistence (Eccles & Wigfield, 2002). In a MOOC environment, persistence is connected with dropping out (Lee & Song, 2022), and research about course completion rates is related to persistence (Alamri, 2022); as in the case of the MOOCs, the expectancy-value theory explores how course participants recognise the expectancy to successfully complete the learning (Lee & Song, 2022). Studying the dropout is more important from the course organisers' perspective as until the dropout, they have supported these learners, for example, by evaluating mandatory activities and giving feedback (Gutl et al., 2014). In addition, dropped-out learners may not gain the educational benefits from the learning experience that was prepared for them in the course (Hone & El Said, 2016).

Course completion is only one metric to define learners' success in MOOCs (Avello et al., 2020), as there is no single definition of success (Padilla Rodriguez, 2020). There is also no common understanding on the basis of which a course participant can be considered a dropout. Requirements for completing the course are set by MOOC organisers, and when learners meet the conditions, they are considered completers (Moreno-Marcos et al., 2020; Pigeau et al., 2019). Dropouts are the course participants who quit the course or cannot meet the thresholds set for course activities (Pigeau et al., 2019). In this thesis dropouts and non-completers are used as synonyms. Researchers have used various selection criteria to include MOOC enrollees in their studies. Sometimes, all learners who enrolled on a MOOC have been considered (de Freitas et al., 2015), or alternatively, the dropout rate has been calculated based on active learners, i.e. those who participated at least in some of the course activities (Ihantola et al., 2020). However, the concept of 'active learners' has also been understood in different ways. One possibility is to consider all course activities regardless of whether or not they are required

to complete the course (Gitinabard et al., 2018). Another way is to take only the mandatory activities into account (Ihantola et al., 2020). Going even further, it has been suggested for MOOCs that are more professional or technical in nature – this would be unsuitable for MOOCs of general interest – that the calculation of dropout rates should be based only on learners who have demonstrated that they can master the course material. For example, the dropout rate in a 9-week course should be calculated out of those learners who have been able to successfully complete the first two weeks of the MOOC, discounting those who left the course in week one or two (Coffrin et al., 2014).

Researchers have also let course participants themselves define what they consider as completion of the MOOC (Eriksson et al., 2017) or whether they dropped out or not (Handoko et al., 2019). For almost all learners, completing a course meant completing all or nearly all course activities (Eriksson et al., 2017). Reported dropout rates may also be influenced by different approaches to setting up research parameters, depending on the characteristics of the course and the research methodology. For instance, researchers can set an inactivity period in days after which learners are unlikely to complete the course (Moreno-Marcos et al., 2020), or they can define the starting point of a MOOC as the week when a learner is active for the first time when different courses in the study start at different times (Lu et al., 2017), or they can limit the study to the official timeframe of a MOOC even if learners can participate outside of it (Vitiello et al., 2018). The lack of a standard definition of dropout makes it challenging to compare the dropout rates in different studies (Goopio & Cheung, 2020).

Expanding the topics of dropout and learners' success even more, the perspective of dropout research has moved from an outcome-based to an individual-based approach (Henderikx et al., 2017). In the expectancy-value theory, expectancies for success show an individual's beliefs on how well the forthcoming task will be done (Eccles & Wigfield, 2020) and these target individual level expectations (Eccles & Wigfield, 2002). Individual level of learners is the basis for researchers who think that measuring learners' success based on completion rates is not adequate (Littlejohn et al., 2016; Stracke, 2017). Using the completion rate as the basis can result in very high dropout rates (Goopio & Cheung, 2020). In a comparison of completion rates and success measured in terms of fulfilling the intentions, the completion rates of the two courses observed were 6.5% and 5.6%, respectively, but 59% and 70% of the course participants were successful as far as their intentions were concerned (Henderikx et al., 2017). In another example, 2% of the participants completed the course, but 51% of the learners fulfilled their own goals (Conijn et al., 2018). Dropout rates only highlight the differences in motivation and personal goals that course participants may have (Stracke, 2017) but do not take the intentions into account (Littlejohn et al., 2016; Padilla Rodriguez, 2020) nor allow learners to determine the basis of their own success (Littlejohn et al., 2016). Learners' intentions have to be included to avoid misinterpreting dropout and success in MOOCs in general and at the individual level (Henderikx et al.,

2017; Stracke, 2017).

How learners perceive the course (Padilla Rodriguez, 2020), and the reasons why they signed up for the course (Kaveri et al., 2016) can be overlooked when learners' intentions are not considered. Learners may simply want to download course materials for future use (Stracke, 2017), audit the course (Reich, 2014), or complete some parts of the course based on their individual needs (Li et al., 2021; Reich, 2014). Not all course participants are interested in earning a certificate (Shapiro et al., 2017). Learners who do not complete the course may still reach some measurable learning outcome (de Freitas et al., 2015). Some course participants do not attempt to do any of the mandatory activities, but they interact with other resources that the course offers (de Barba et al., 2020). In MOOCs, it is convenient to explore the content that interests learners and not to complete every aspect of the course since there is no obligation to finish the courses (Shapiro et al., 2017). Participants may seem underperforming if they do not visit course content often, but they may already be familiar with it (Fei & Yeung, 2015). Therefore, it has been suggested that learners should be considered successful if they do what they intended to do or more. Conversely, course participants who do less than they initially planned or who leave a MOOC in the middle of the course run would be considered unsuccessful and dropouts (Henderikx et al., 2017). If learners' intentions have been established, it is easier to understand why they leave the course (Goopio & Cheung, 2020).

In summary, learners' success in MOOCs can be approached differently, and success can mean different things from the perspective of course organisers and course participants. For researchers, learners' success has primarily been equated with completing the course. This is also of interest to course organisers. Another approach would be to consider the individuality of course participants, i.e. to evaluate success based on learners' intentions related to the course. On the one hand, the different approaches make it difficult to compare research results. On the other hand, given the specifics of MOOCs, it also highlights the need to study learners' success from the point of view of both course participants and organisers, i.e. fulfilling learners' intentions as one aspect and dropout as the other aspect.

2.2. Dropout time

The time when dropout happens and learners' performance up to this point are two essential characteristics of MOOC dropout. This knowledge gives course organisers information about the moments when learners should be supported the most and input for possible changes to be made in the course design to help learners get through those points. In the view of the expectancy-value theory, Brophy (2013) has indicated that effort results from the combined effect of both expectancies and value. If one of these factors is missing, one is unwilling to invest any effort. Therefore, dropout occurs when learners do not value the course activities or do not achieve success in these activities when investing a reasonable effort. In

the current thesis, completion of mandatory course activities every course week has been used as a measure of learners' performance. Performance is also a factor that can be affected by expectancies and value according to the expectancy-value theory (Eccles & Wigfield, 2002).

Regarding dropout time, learners may leave the course even before the course starts (Perna et al., 2014; Vitiello et al., 2018) or before the deadline of the first activities (de Freitas et al., 2015). Some participants visit only the introductory section of the course and then leave (Zhang et al., 2021). Learners tend to drop out before or halfway through the course (Hone & El Said, 2016; Reparaz et al., 2020; Sujatha & Kavitha, 2018). Specifically, in 4–7-week courses, participants tend to quit more at the beginning of the course (de Freitas et al., 2015; Ihantola et al., 2020), and, based on a survival analysis of 4–11-week courses, the highest probability of dropping out occurs in the first learning week (Greene et al., 2015). By the end of the second week, more than half of active learners had dropped out (Greene et al., 2015). Some course participants complete all the mandatory activities in the first week but do not continue with the course in the second week. These may be the kind of learners who put total effort into something they have started but have problems with starting the activities (Ihantola et al., 2020).

Most MOOC participants who get past the mid-point of the course complete it (Hone & El Said, 2016). However, the number of active learners in a course can decrease week by week (Coffrin et al., 2014). In a 9-week course, the number of active learners started to stabilise from the 6th week (Mourdi et al., 2019), and the dropout rate stabilised to almost negligible by the end of a 4-week course (de Freitas et al., 2015). At the beginning of a MOOC, participants know less about the content of the course (Lu et al., 2017) and may leave when they discover that their circumstances are incompatible with the course (de Freitas et al., 2015; Ihantola et al., 2020; Lu et al., 2017; Zhang et al., 2021), the schedule (Zhang et al., 2021) or the workload (Ihantola et al., 2020). It can also indicate that learners came to the course out of curiosity (Perna et al., 2014) and only experimented with the course activities (Coffrin et al., 2014). MOOC participants without the interest or motivation to finish the course leave (Perna et al., 2014), whereas dedicated learners continue until the end (Coffrin et al., 2014).

The number of dropouts can also be high at the end of the course (Lu et al., 2017; Reparaz et al., 2020). Chen et al. (2019) found that dropout rates were higher in the last two weeks of a 5-week course compared to the first three weeks. Learners can even leave a course after completing all relevant course activities except the last one, which they do not submit (Sabanwar et al., 2022), or they quit because of the exam (Lu et al., 2017). This may indicate that the course did not give learners sufficient preparation for the final activity (Kinnunen & Malmi, 2006). Leaving a course before the end means these participants still would have learned some concepts (Sabanwar et al., 2022). However, some learners become more active at the end of the course and are keen to do the mandatory activities. It may suggest that the participants who have worked hard for the course do not

want to give up at the end (Hone & El Said, 2016) or finish without a certificate (Hone & El Said, 2016; Vitiello et al., 2018).

In summary, previous research has yet to show consistent results regarding dropout time. On the one hand, several studies show that the first weeks of the course have the highest number of dropouts, and then the number stabilises. On the other hand, there are also courses where the dropout rate is highest at the end of the course. As these tendencies appear regardless of the MOOC topic (e.g. de Freitas et al., 2015; Ihantola et al., 2020; Lu et al., 2017; Perna et al., 2014; Reparaz et al., 2020) and dropout has been studied by including multiple MOOCs with different topics without distinguishing between topics (e.g. Perna et al., 2014; Reparaz et al., 2020), there is no differentiation of the topics of MOOCs in this thesis. Given that the studied MOOCs differ, including in terms of duration, it is also difficult to compare the results between the studies. The conflicting results make it necessary to investigate the periods with the highest dropout rates.

2.3. Factors affecting learners' success

Knowing which factors influence dropout is essential to understand why learners are or are not successful in MOOCs. The expectancy-value theory contains various factors that may have an impact on the success of learners. As previously stated, the expectancy-value theory consists of two main components – expectancies and value, and these influence performance and persistence. In addition, authors of this theory have also reflected on factors which directly or indirectly affect expectancies and value (Eccles et al., 1983). Two of these, background characteristics and prior experiences, are relevant to this thesis as anyone who wishes can participate in MOOCs and no previous qualification is required. Therefore, MOOC participants may have the most diverse experiences and backgrounds out of all learning contexts (Li, 2019). In addition, according to previous research (Chaker & Bachelet, 2020; Chen et al., 2020a; Greene et al., 2015), learners' success has been affected by these two factors.

In the expectancy-value theory, value is divided into four subcomponents (Eccles et al., 1983), and the first two are the most salient in the MOOC context (Chen et al., 2020b). Intrinsic (or interest) value expresses enjoyment gained from doing an activity (Eccles et al., 1983). In a MOOC environment, it is interpreted as learners' interest in participating in the MOOC and their enjoyment of it (Chen et al., 2020b). Utility value reflects interest in the subject and the connection between a task and goals, including current and future (Eccles et al., 1983) and short- and long-term (Eccles & Wigfield, 2002) goals. In MOOCs, it can be taken as the usefulness of participating in MOOCs for fulfilling external goals (Chen et al., 2020b). As MOOCs are optional for learners, it can be challenging to see the value or importance of these courses (Goegan et al., 2021). The importance attached to the performance of various tasks and activities is shown by the attainment value. In sum, these three value subcategories help learners understand the

positive parts of the value (Eccles et al., 1983) of MOOCs. Through these, it is possible to describe the motivations why learners enrol on MOOCs (Lee & Song, 2022). It is important to study the motivation of enrolling on MOOCs as it allows seeing in advance the possible barriers and benefits that learners may experience (Maya-Jariego et al., 2020) and motivation to enrol is one of the factors that affect the completion of MOOCs (Luik et al., 2018). Therefore, among the various approaches to how motivation has been studied in the context of MOOCs, the motivation for enrolling in a course is used in this thesis.

The only negative aspect of the value and doing the task is cost (Eccles et al., 1983) which has been less studied than other value components (Eccles & Wigfield, 2020; Lee & Song, 2022). Cost has negatively predicted the perception of learners' success (Goegan et al., 2021) and has been seen as the leading cause of why learners drop out of MOOCs (Lee & Song, 2022). Cost includes psychological cost (Eccles et al., 1983) that shows emotional toll, e.g. anxiety (Nagle, 2021), the effort required to succeed, and the opportunities lost because of doing that particular task (Eccles et al., 1983). In a MOOC environment, learners give up when the perceived learning costs are high (Lee & Song, 2022). Cost in the MOOC context is related to overcoming the obstacles to achieve the set goals and invested time (Chen et al., 2020b). How learners manage their time is considered one of the crucial aspects that affect learning in MOOCs (Lee et al., 2019) and poor time management has been seen as the main reason for dropout (Nawrot & Doucet, 2014). Therefore, learners' use of time for the MOOC is considered in this thesis a cost of participating in the course.

In addition to learners' performance and their learning continuance, expectancies and value affect how learners choose tasks (Eccles & Wigfield, 2002) and through the choice of the tasks, also their sequence of the tasks (Chen et al., 2020b). Learners engage in tasks they like or find interesting, perceive as beneficial and personally meaningful, but evade tasks seen as costly (Beymer et al., 2022). In this thesis, tasks are defined as different course activities that are prepared for learners by course organisers to explain the topic, assess their knowledge, provide support and for other purposes. In MOOCs, learners do not have to follow the order of activities set by course organisers (Wong et al., 2019) and can create their learning path (Littlejohn et al., 2016; Onah et al., 2021; Perna et al., 2014). Therefore, knowing why learners make different choices and how these affect their success in MOOCs is relevant.

As Jiang and Zhang (2023) have concluded, based on previous research, learners' engagement is another aspect that is affected by expectancies and value. It is relevant for this thesis as in a MOOC environment, engagement is considered a central determinant of learners' success (Anutariya & Thongsuntia, 2019) and, therefore, it has affected course completion (Badali et al., 2022; Semenova, 2022).

In summary, for this thesis, five different factors have been selected which, based on the results of previous studies, have influenced learners' success in MOOCs, and which derive from the expectancy-value theory or are affected by

expectancies and value. These factors are learners' background data and previous experience, motivation to enrol on a MOOC, use of time in the course, learners' choices regarding course activities, and engagement. The following sub-chapters discuss these factors and the impact of these factors on the success of learners, mainly from the perspective of dropping out of the course.

2.3.1. Learners' background characteristics and previous experience

Given that no demographic or previous educational experience restrictions are set for learners to participate in MOOCs, learners in MOOCs differ in these factors. If age is considered, then survival (Chen et al., 2020c; Greene et al., 2015) and logistic regression analysis (Reich, 2014) have shown that older learners are less likely to drop out. More specifically, Huang and Hew (2017) found in a comparison of different age groups that course participants under 30 dropped out more than older learners. The reasons why younger participants drop out more may be related to them coming to MOOCs out of curiosity. However, older learners have specific reasons for enrolling, e.g. professional development (Huang & Hew, 2017). MOOC participants have pointed out that they completed the course because it was useful for them, e.g. for their career (Eriksson et al., 2017). In addition, Luik et al. (2019a) showed based on one of their courses that younger learners are more likely to drop out before the course even starts. Age did not influence learners' success when it was studied based on learners' intentions (Chaker & Bachelet, 2020).

In dropout research, on the one hand, no significant differences in completion rates by gender have been found (Hone & El Said, 2016). On the other hand, survival analysis has shown that gender has been the main predictor of dropout at the beginning of MOOCs (Chen et al., 2020a). There are studies that have found men to be more likely to stay longer on a MOOC compared to women (Cruet et al., 2018; Guajardo Leal & Valenzuela González, 2019; Reich, 2014). Luik et al. (2019a) found in their MOOCs with different difficulty levels that there were no gender differences in course completion in the easier courses, but men were more likely to complete the more difficult ones. Women had lower dropout rates when the dropout rate was calculated based on learners' intentions (Chaker & Bachelet, 2020).

The educational level has been shown to be affecting dropping out in multiple dropout-related studies. Based on the results of survival (Greene et al., 2015) and logistic regression analysis (Reich, 2014), it seems that more educated learners are less likely to leave a course. More specifically, course participants with a bachelor's degree or higher (Guajardo Leal & Valenzuela González, 2019) or master's degree or higher are less likely to drop out (Gomez-Zermeno & Aleman de La Garza, 2016). Rawat et al. (2021) found that learners with a doctoral degree dropped out the least. When the impact of prior education on dropout was studied across MOOCs with different difficulty levels, the results showed that in the case

of the easier MOOCs, participants with a master's degree had a higher likelihood of completing the course than learners with lower educational levels. The biggest group of completers in a more difficult course consisted of participants with basic education (Luik et al., 2019a). When learners' intentions were taken into account in calculating the dropout rate, no correlation between the level of education and dropout was found (Chaker & Bachelet, 2020).

Learners have reported previous bad experiences with the topic, insufficient knowledge, and difficulties with working in an online learning environment as barriers to completing MOOCs (Shapiro et al., 2017). Although Greene et al. (2015) found in their survival analysis that previous knowledge about the topic had no influence on dropout, other researchers (Chen et al., 2020c; Reich, 2014) have shown that learners who were more familiar with the topic had lower odds of leaving the course. Previous experience with the topic helps MOOC participants as they are more motivated to do well and have more confidence in their skills and success (Alonso-Mencía et al., 2021). Chen et al. (2020a) found that prior knowledge affects learners only at the beginning of the course, as after dealing with the course content, course participants without previous experience are as engaged as learners with prior experience. When the level of difficulty of the course was considered, then participants in easier courses were less likely to complete the course if they did not have previous experience with the topic (Luik et al., 2019a).

Research of previous experience in online courses, including MOOCs, in relation to dropout, has found, on the one hand, with binary logistic regression that learners who participated in their first MOOC were more likely to complete it (Guajardo Leal & Valenzuela González, 2019). On the other hand, course participants without previous experience in online education (Gomez-Zermeno & Aleman de La Garza, 2016) or more specifically in MOOCs have been found to drop out more. It has even been observed that previous experience in learning in MOOCs can be the strongest predictor of dropout (Greene et al., 2015). Lack of feedback (Sujatha & Kavitha, 2018) and technical skills (Gomez-Zermeno & Aleman de La Garza, 2016) and insufficient contact with course organisers and other learners have been noted as reasons why MOOC participants did not finish a course (Khan et al., 2021; Sujatha & Kavitha, 2018). Previous experience in an online learning environment may help course participants feel comfortable, and these learners are more confident in completing MOOC activities and the course (Lee et al., 2019).

In summary, previous research suggests that learners' background and prior experience influence their success in MOOCs, which has mostly been measured by dropout rates. In addition, based on different studies, the results show that these factors can have contradictory impacts on success. It highlights that learners with a broad range of characteristics can participate in MOOCs, and the influence of their backgrounds and experiences on success needs to be studied further. In addition, since success can be assessed through different approaches, it is also important to know how the factors that affect dropout affect success when it is

measured based on the intentions of course participants. This knowledge can provide course organisers with an opportunity to support learners more purposefully in fulfilling their intentions.

2.3.2. Motivation to enrol

According to a systematic literature review, motivation in MOOCs has been studied based on different motivation theories, like self-determination and expectancy-value theories (Badali et al., 2022). Not only are there various motivation theories that can be used, but there are also different ways to define motivation. Many definitions are based on the concept of movement (Elliot & Zahn, 2008), indicating that being motivated means being moved to do something (Ryan & Deci, 2000). According to Elliot and Zahn (2008, p. 687), motivation is “the energization and direction of behavior”. It is assumed that people will begin to behave or continue to behave in a way that will lead them to desired outcomes or goals (Deci & Ryan, 2000). To explain motivated behaviour, the focus should be on the reasons that make a person behave in one way or another and on the specific goals that people focus on in directing their behaviour (Elliot & Zahn, 2008). People can have various degrees of motivations and a range of attitudes and goals that are the ground of action (Ryan & Deci, 2000). Diverse goals lead to different behavioural outcomes (Deci & Ryan, 2000).

Motivation plays a leading role in learners’ learning outcomes in different learning environments (Shapiro et al., 2017), and motivation differs for participants in MOOCs and in regular courses (Williams et al., 2018). In the case of MOOCs, learning is more dependent on motivation (Chen et al., 2020d). Motivation drives the choice of a MOOC and the participation (Semenova, 2022) as it is easy for learners to enrol and leave these courses (Chen et al., 2020d). Studies have shown conflicting results on the effect of motivation on MOOC completion as on the one hand, highly motivated learners seem to be more likely to complete the course (Chen et al., 2020a; Huang & Hew, 2017). On the other hand, it has been found that course participants with high motivation at the beginning of the course drop out more (Luik & Lepp, 2021). This may be explained by the fact that differences have been found in terms of the motivation to enrol in a MOOC between completers and non-completers (Luik et al., 2018; Reparaz et al., 2020).

The main reason why learners participate in MOOCs is their interest in gaining knowledge about the respective subjects (Chen et al., 2020d; Shapiro et al., 2017). This reason occurs more for course completers than non-completers (Reparaz et al., 2020). The knowledge can be required for personal reasons, studies (Chen et al., 2020d; Zheng et al., 2015) and for a current or future job (Shapiro et al., 2017). Even if learners need the knowledge, there are reasons like family life (Aydin & Yazici, 2020; Eriksson et al., 2017), work (Aydin & Yazici, 2020; Semenescu et al., 2020) and other studies (Aydin & Yazici, 2020) that can prevent learners from completing the MOOCs. For example, people can sign up for a MOOC at a time

when they have few other responsibilities, but the emergence of such responsibilities that demand learners' resources during the course can cause dropout (Zheng et al., 2015). The same outcome occurs when learning in a MOOC is not supported at the workplace (Gutl et al., 2014). Nevertheless, both completers and dropouts are motivated to take the MOOCs because they believe that they are able to balance studies with work and family life (Luik et al., 2018).

Another reason why people enrol on MOOCs is curiosity about the course and a wish to know how learning takes place in a MOOC (Chen et al., 2020d; Semencescu et al., 2020). Logistic regression has shown that learners who participate in a MOOC out of curiosity are more likely to finish the course (Semenova, 2022). However, learning in MOOCs can create obstacles that make participants leave these courses. For example, learners can feel isolated and unmotivated without enough communication and feedback from course organisers and fellow participants (Hone & El Said, 2016; Khan et al., 2021). Yet, networking with learners who have similar interests is one of the reasons for coming to a MOOC (Chen et al., 2020d; Williams et al., 2018). Learners also drop out when the course is badly organised, the workload is too high (Semencescu et al., 2020), or the content is not what was expected (Eriksson et al., 2017) or turns out to be too challenging (Zheng et al., 2015). Given that a MOOC is an online course, suitability of such courses for the learners' personality can have a stronger correlation with the motivation to enrol in the case of completers (Luik et al., 2018). Course participants with stronger digital literacy are more likely to complete MOOCs (Khan et al., 2021).

Notably, getting a certificate seems to rank relatively low among the reasons for enrolling on a MOOC, both for completers and non-completers (Reparaz et al., 2020). Studies have shown mixed results on how motivation to earn a certificate can affect dropout. On the one hand, the prospect of a certificate can motivate learners to complete a course (Huang & Hew, 2017), and it has been shown that dropout rates are higher among those course participants who are not interested in a certificate (Chen et al., 2020c; Luik et al., 2018). The importance of a certificate can be linked to the learners' belief that MOOC certificates increase their chances in the job market (Elsayed Mohamed & Ali, 2018). Second, according to a correlation analysis, learners with a higher tendency to complete the MOOC are less likely to depend on external factors like certification (Romero-Rodríguez et al., 2020). Also, it has been pointed out that the intention to complete the course is not related to actual completion (Luik & Lepp, 2021). Sometimes, learners that do not intend to complete a course may actually do it (Luik & Lepp, 2021; Reich, 2014). Conversely, learners with the highest motivation to enrol (Luik & Lepp, 2021) and an intention to complete the course (Reich, 2014) may drop out.

A learner's perceived success in a course in the eyes of their family and friends is one of the least important reasons why participants come to MOOCs (Luik et al., 2019b), but it is more motivating for the ones who complete the course (Luik et al., 2018). However, people can enrol on MOOCs if their friends recommend

the courses (Elsayed Mohamed & Ali, 2018). When the recommending person does not complete the course, those who took the recommendation tend to find excuses for not completing it as well (Zheng et al., 2015).

In summary, in the context of MOOCs, it is important to study the motivation of enrolment because, considering the specifics of these courses, it is easy for learners to enrol and leave MOOCs, and it helps to identify possible problems and advantages early on. There are various motivational factors why learners enrol in MOOCs, which have also influenced dropout rates. In addition, it has been found that dropouts and completers can enrol in a MOOC for different reasons. However, previous research has given conflicting results on how the motivation to enrol affects course completion. As the research on this topic has mainly been based on measuring dropout, it is important to expand the research on learners' success and study the effect of enrolment motivation on success defined in terms of learners' intentions.

2.3.3. Use of time

Lack of time is one of the most cited reasons why participants do not complete MOOCs and is mainly caused by insufficient time management skills. After a review of existing literature, time management has been defined as “behaviours that aim at achieving an effective use of time while performing certain goal-directed activities” (Claessens et al., 2007, p. 262). It is a common problem for many learners in an environment with greater autonomy, like MOOCs (Onah et al., 2022). Relying on previous studies, Claessens et al. (2007) have identified three behaviours that help to perform goal-directed activities through effective time use, and these are described below.

First, time assessment behaviours include self-awareness of time use and awareness of past, present, and future. These influence taking on tasks and responsibilities within one's capacity. In a MOOC environment, the amount of time that participants need to spend on a university-level course can be a lot greater than expected, and they may not be prepared for this (Shapiro et al., 2017). For better time management, experience with online learning has been helpful as learners can use different technological tools to help them manage their time (Goodson et al., 2016).

The second category, planning behaviours, includes activities to facilitate efficient use of time, such as setting goals and priorities (Claessens et al., 2007). Learners may understand the need for short-term time planning while overlooking the long-term (Sainz et al., 2019). Often, time is allocated for learning activities based on which deadline is the closest (Onah et al., 2022; Sainz et al., 2019) and any activities that do not need to be done at the present moment are put on hold without any planning (Sainz et al., 2019). The selection of activities can also depend on the importance of the content and the topics that interest learners (Onah et al., 2021). In general, compared to other responsibilities, MOOCs tend to be

regarded as a hobby or entertainment, and learning on a MOOC is not the first priority (Eriksson et al., 2017).

Third, monitoring behaviours include monitoring and feedback on one's own time use that can reduce the impact of interference caused by others (Claessens et al., 2007). MOOCs have shown that learners perform better if they can overcome delays and distractions to fulfil their goals (Li et al., 2022). Work (Eriksson et al., 2017; Onah et al., 2022; Shapiro et al., 2017), family obligations, other studies (Eriksson et al., 2017), social activities and hindrances that are caused by learning in an online environment (Onah et al., 2022) are among the factors that compete for the time participants can spend on learning in a MOOC.

Most MOOCs have a recommended amount of time that learners should spend on the course, but participants are free to act based on their schedule and learn at their own pace (Khalil & Wong, 2018). In MOOCs, learners try to stay on the course but use less time than organisers have planned (Shapiro et al., 2017). The amount of time allocated for learning does not always affect the outcome, as there are participants who spend less time on the course but are as successful as the learners who spend more time (Mubarak et al., 2021). However, learners do perform better when they invest enough time in MOOCs (Li et al., 2022). The way time is used has affected course completion. The participants who start learning earlier are more likely to stay until the end of the course (Lu et al., 2017; Rawat et al., 2021). Scheduling the time can vary, as some learners plan to take time for the course daily while others intend to learn on a specific night of a week (Ding & Shen, 2022). Flexibility is more essential than regularity, as managing study time flexibly can take more effort than learning regularly (Li et al., 2022). Compared to dropouts, completers spread their learning over more days (Conijn et al., 2018) and they have more and longer study sessions (de Barba et al., 2020; Lee, 2018). There is also a correlation between course content and time management. The amount of time and effort required to acquire the learning content depends on the volume (Shapiro et al., 2017) and difficulty (Tabuenca et al., 2022) of the content. The participants who complete the same amount of learning activities in fewer sessions are more likely to complete the course (Lee, 2018). If participants do not follow the suggested sequence of learning activities in a MOOC, it is often due to poor time management (Chen et al., 2020b).

In summary, MOOCs give participants the freedom to choose how they use the time they spend studying. Previous research has also shown that learners allocate time differently in MOOCs. Although some learners spend less time in the course and are still successful, most learners are not prepared for the time requirements of learning on a MOOC. To manage time successfully, one has to choose activities according to their abilities while also planning and monitoring the activities. Previous studies have looked at the reasons that affect dropout from MOOCs, with lack of time being the main reason. However, what influences the use of learners' time has been less studied. Therefore, it is essential to know how learners perceive their use of time and which factors affect it.

2.3.4. The sequence of course activities

MOOCs allow learners to choose what course activities they participate in and the order in which they do the activities. Learners who follow the sequence set by course organisers find it suitable for their learning habits (Onah et al., 2021). Course participants tend to choose activities based on their needs (Zheng et al., 2015) and focus on the parts of the course that are practical and useful (Ding & Shen, 2022). Learners want activities that challenge them (Hew, 2018). It is also possible to skip learning activities (Wong et al., 2019). In MOOCs, some learners do not participate in all activities (Janakiraman et al., 2018), possibly because they lack the skills required for some of the activities (Albelbisi, 2019) or, on the opposite, they may skip some activities because they already know the material (Jansen et al., 2022). Learners may also want to interact with learning materials without doing the mandatory activities (Zheng et al., 2015) or only perform the mandatory activities and skip the activities that are meant for practice (Coffrin et al., 2014).

Based on one activity, MOOC participants may choose other activities to perform. For example, the content of quizzes can guide learners' decisions on which videos to watch (Zhang et al., 2021). Course participants can use the opportunity to engage in one activity multiple times (Conijn et al., 2018). The open course structure allows moving forwards and backwards between the activities. Learners revise previously completed activities (Coffrin et al., 2014) and learning materials from previous weeks (Conijn et al., 2018). These materials are revisited after failing mandatory activities before retaking these activities (Janakiraman et al., 2018). The occurrence of problems also affects the use of course activities. For these learners, a forum can be essential (Lee et al., 2019). It has been observed that forums are not used often (Conijn et al., 2018; Janakiraman et al., 2018) and their use tends to be conditional on having a direct benefit to learners (Janakiraman et al., 2018), but they can also be used for sharing knowledge and creating a community (Cruet et al., 2018). Many MOOC participants cannot monitor their learning process (Jansen et al., 2022), but some of them can change their learning path over time to meet their personal needs (Littlejohn et al., 2016). Successful learners can change the priority of the activities during the learning sessions (de Barba et al., 2020).

Regarding course completion, on the one hand, no difference has been found between completers and dropouts regarding the way they browsed the course (Pigeau et al., 2019). On the other hand, completers try to comply with the schedule suggested by course organisers even if they progress at a slower pace and need a few extra weeks to complete the course (Moreno-Marcos et al., 2020). The learners who participate in more learning activities are more likely to complete the course (Lee, 2018). Before exams, completers tend to work more with materials from previous weeks, revisit more course activities and start this revisiting process earlier than dropouts (Conijn et al., 2018).

In summary, MOOCs allow participants to create their individual learning path by choosing course activities and the manner of their usage. As a results, there are differences between learners in terms of their behaviour related to course activities. To create a learning environment that is suitable for all MOOC participants, it is necessary to know how learners engage in course activities and what are the reasons for making those choices.

2.3.5. Engagement

Although learners' engagement has been studied for decades, no single definition has been established (Guajardo Leal & Valenzuela González, 2019). Engagement in the learning environment has been viewed as the level at which learners are involved in their learning process or the tools available (Perez-Alvarez et al., 2020). According to one definition, learning engagement in a MOOC environment means "the mental energy and effort that learners put into the MOOC learning process to achieve desired performance" (Jung & Lee, 2018, p. 11). Engagement includes different dimensions of involvement in learning activities (Deng et al., 2019). According to Appleton et al. (2006) engagement consists of cognitive and psychological engagement. When engagement has been divided into three dimensions, these have been identified as behavioural, cognitive and emotional dimension (Fredricks et al., 2004). Deng et al. (2019) have added social engagement as the fourth dimension. Out of the different dimensions, behavioural engagement is considered highly important for academic success and dropout prevention (Fredricks et al., 2004).

In MOOCs, engagement is often defined in terms of behavioural engagement and its characteristics are used to measure learners' engagement. The idea of behavioural engagement is based on learners' participation, including participation in social, academic, and extracurricular activities (Fredricks et al., 2004). Engagement in MOOCs has been measured by the completion rate of the activities (Anutariya & Thongsuntia, 2019; Guajardo Leal & Valenzuela González, 2019; Semenova, 2022), which may include watching video lectures, participating in a forum and completing quizzes (Kaveri et al., 2016) or other mandatory activities (Anutariya & Thongsuntia, 2019). In the current thesis, engagement is defined as the amount of different course activities that learners plan to do during the course.

Completing quizzes and other mandatory activities is usually a prerequisite for completing the course. Therefore, it is logical that the number of completed mandatory activities helps to predict course completion until the end of the course (Isidro et al., 2018). Most learners are interested in doing the mandatory activities, but fewer learners actually do them in reality (Moreno-Marcos et al., 2020). In relation to completing activities, the number of times activities are submitted has also affected dropout. It is one of the relevant dropout predictors at the beginning of a course (Isidro et al., 2018), and it has been shown that course participants who submitted activities multiple times were less likely to drop out (Chen et al.,

2020a).

Videos are considered to be the main learning activity in MOOCs (Kim & Park, 2022), and learners who have completed the course have also watched most of the videos (Isidro et al., 2018). It is characteristic for dropouts to only watch videos and not participate in any of the mandatory activities (Moreno-Marcos et al., 2020). These may be the kind of learners who see the MOOC as entertainment and watch videos in their spare time (Zheng et al., 2015). However, no difference in viewing videos has been found between completers and non-completers (Kim & Park, 2022). Watching videos has a stronger impact on MOOC completion than reviewing videos (Moreno-Marcos et al., 2020). At the beginning of the course, the number of times videos were rewound was one of the most relevant factors in predicting dropout (Isidro et al., 2018). Watching videos multiple time makes learners feel inadequate and left behind, which may lead to dropping out (Zheng et al., 2015). In addition to the videos, reading materials are used as complementary learning resources (Deng & Benckendorff, 2021) or as the main learning material (Lepp et al., 2017). It has been found that completers use reading materials more than non-completers (Kim & Park, 2022).

Learners that are more engaged participate more in the social aspects of a course, including discussions (Guajardo Leal & Valenzuela González, 2019). A forum is essential to foster communication between course organisers and learners (Tang et al., 2020). No noticeable differences in forum usage have been observed between completers and non-completers (Kim & Park, 2022; Vitiello et al., 2018). However, the learners who participate in a forum (Semenova, 2022), more specifically by commenting (Tang et al., 2020) or posting (Crues et al., 2018; Tang et al., 2020) to the forum, are more likely to stay on the course compared to those who do not. In addition to a forum, weekly update letters and videos can be used for communication. From these letters, learners have found encouragement to continue the course (Lepp et al., 2017), and videos can help resolve problems that may be encountered, which has a positive effect on finishing the MOOC (Eriksson et al., 2017).

In summary, studying engagement in MOOCs has often been done through behavioural engagement, considering the completion rate of various course activities. The manner and extent of learners' engagement in different course activities has also affected their course completion. However, there is a lack of research examining engagement's impact on learners' success if success is conceptualised in terms of learners' intentions. Therefore, research should also focus on this direction.

The main concepts used in this thesis are summarised in Table 1. Table 2 provides an overview of the research questions and the factors studied in association with the research questions, as well as the main references related to the factors.

Table 1: Main concepts of the thesis

Concept	Definition
Completer	A learner who completed all mandatory course activities
Dropout/ non-completer	A learner who did not complete all mandatory course activities
Dropout week	The last week when learner submitted at least one of the mandatory activities
Engagement	The amount of different course activities that the learner plans to do during the course
Expectancy	People's beliefs about how well they will perform in a task
Performance	Completion of mandatory course activities every week
Success based on learners' intentions	Overlap between a learner's intention for the course and actual performance: Successful learner – a learner who completed as many or more course activities than intended Unsuccessful learner – a learner who completed less course activities than intended
Success based on course completion	Completion of all mandatory course activities Successful learner – completer Unsuccessful learner – non-completer
Task	Course activity that is prepared for learners by the organisers to facilitate learning a topic, assess their knowledge, provide support and for other purposes
Value	The extent to which a task helps a person to meet their needs and goals

Table 2: Overview of the research questions, related factors and main references

Research questions	Factors	References
RQ1: During which periods do learners drop out of CP MOOCs the most?	Performance before and during dropout week	Chen et al. 2019; de Freitas et al., 2015; Greene et al., 2015; Hone & El Said, 2016; Ithantola et al., 2020; Lu et al., 2017; Mourdi et al., 2019; Perna et al., 2014; Reparaz et al., 2020; Zhang et al., 2021
RQ2: How do dropouts perform before the end of the dropout week in terms of successful completion of mandatory activities in CP MOOCs?	Performance before and during dropout week	Hone & El Said, 2016; Kinnunen & Malmi, 2006; Lu et al., 2017; Sabanwar et al., 2022; Vitiello et al., 2018
RQ3: Which factors affect learners' success based on their intentions in CP MOOC?	Learners' background characteristics and previous experience	Chaker & Bachelet, 2020; Chen et al., 2020a ; Chen et al., 2020c; Crues et al., 2018; Greene et al., 2015; Hone & El Said, 2016; Huang & Hew, 2017; Lee et al., 2019; Luik et al. 2019a; Rawat et al. 2021; Reich, 2014; Sujatha & Kavitha, 2018
	Motivation to enrol	Chen et al., 2020d; Hone & El Said, 2016; Luik & Lepp, 2021; Luik et al., 2018; Reparaz et al., 2020; Zheng et al., 2015
	Engagement	Chen et al., 2020a; Isidro et al., 2018; Kim & Park, 2022; Moreno-Marcos et al., 2020; Semenova, 2022; Tang et al., 2020
RQ4: How do learners perceive their usage of time and the factors affecting it in a CP MOOC?	Use of time	de Barba et al., 2020; Ding & Shen, 2022; Eriksson et al., 2017; Lee, 2018; Li et al., 2022; Lu et al., 2017; Mubarak et al., 2021; Onah et al., 2022; Sainz et al., 2019; Shapiro et al., 2017
RQ5: How do learners describe their sequence of completing the course activities and their justifications for this preference in CP MOOCs?	Choices regarding MOOC activities	Coffrin et al., 2014; Conijn et al., 2018; Janakiraman et al., 2018; Jansen et al., 2022; Lee, 2018; Littlejohn et al., 2016; Moreno-Marcos et al., 2020; Onah et al., 2021; Pigeau et al., 2019; Zhang et al., 2021; Zheng et al., 2015

3. RESEARCH METHODOLOGY

The following chapter describes the methodology used for the research. First, an overview of the research design is presented, followed by an explanation of the study context. The next sections cover the process of data collection, the sample, and the data analysis methods used. The sample, data collection and analysis methods are presented in Table 3 for individual research questions. The abbreviations for the CP MOOCs relevant to this study are as follows:

- AP18 – “About Programming” course (hereinafter, AP), that was organised in the autumn of 2018;
- AP19 – AP course that was organised in the spring of 2019;
- IP1 – “Introduction to Programming 1”;
- IP2 – “Introduction to Programming 2”.

Mixed-methods research was used to achieve the aim of the thesis and find answers to the research questions. Mixed-methods research integrates the strengths of quantitative and qualitative methods. It enables a more complete understanding of the phenomenon by combining learners’ experience with a more generalisable and wider qualitative analysis (Guetterman et al., 2019). More precisely, quantitative dominant mixed methods research is used based on the research questions. In this method, the focus is on the post-positivist view of the research process while considering the benefits the qualitative approach adds to the quantitative research (Johnson et al., 2007). The qualitative part of the research allows the subjects to express their feelings and what they do and think they believe (Kaae & Traulsen, 2020). This thesis used a qualitative approach in the previously mentioned context to collect data from different cycles of the MOOCs’ lifespans to interpret the quantitative results.

3.1. Research design

Several models have been created to study learners’ dropout at the higher education level (e.g., Bean, 1985; Tinto, 1975). However, these models may not be appropriate in the context of MOOCs. For example, Tinto’s model (1975) was created to study dropout as a longitudinal process. This may lead to a situation where the effect of different factors, such as Intellectual Development, may not appear due to the relatively short duration of MOOCs. In MOOCs, learning is only online, and often, the connection with other learners and course organisers does not emerge or is superficial. However, the mentioned models include a variety of learners’ connections, including extracurricular activities (Tinto, 1975), contact with faculty (Bean, 1985; Tinto, 1975), the learner’s individual impression of the correspondence to the values and norms of peers and mentors and loyalty to the institution (Bean, 1985) which are unlikely to occur in the environment of MOOCs. In addition, these models focus only on the dropout. As discussed in the

Table 3: Overview of the research questions, sample, data collection and analysis methods

Research questions	Sample	Data sources	Data analysis methods
RQ1: During which periods do learners drop out of CP MOOCs the most?	Active learners of four courses: 1,042 from AP18 841 from AP19 1,375 from IP1 605 from IP2	Moodle learning management system (Moodle)	Descriptive statistics of the dropouts, McNeimar's test for comparison
RQ2: How do dropouts perform before the end of the dropout week in terms of successful completion of mandatory activities in CP MOOCs?			Descriptive statistics for dividing learners into groups, Z-test for proportion comparison
RQ3: Which factors affect learners' success based on their intentions in CP MOOC?	834 respondents of pre-questionnaire of AP19	Moodle, pre-questionnaire, Study Information System	Decision tree with the CHAID growing method
RQ4: How do learners perceive their usage of time and the factors affecting it in a CP MOOC?	1,040 respondents of pre- and post-questionnaires of AP18 and AP19 Sub-sample: 24 writers of learning diaries	Learning diaries, pre-questionnaire, post-questionnaire	Inductive content analysis, descriptive statistics of evaluations, Wilcoxon signed-rank test for comparison, Mann-Whitney U-test for ratings comparison
RQ5: How do learners describe their sequence of completing the course activities and their justifications for this preference in CP MOOCs?	1,003 respondents of pre- and post-questionnaires of AP18 and AP19 Sub-sample: 24 writers learning diaries		Inductive content analysis, descriptive statistics of evaluations, Mann-Whitney U-test for ratings comparison, Chi-square test for proportion comparison

literature review, intention-based success is also relevant to MOOCs. Therefore, this thesis revolved around the following model (Figure 1) developed based on a literature review. Relying on the expectancy-value theory (Eccles et al., 1983), the model represents how different factors affect learners' success in MOOCs according to the two approaches considered. Therefore, the approaches to success and the factors affecting learners' success are divided into three categories: factors that affect expectancies and value, expectancies and value, and factors that are affected by expectancies and value.

The first approach to learners' success is defined by course completion, and in the expectancy-value theory framework (Eccles et al., 1983), it represents learners' persistence that is affected by expectancies and value. Course completion is relevant to this thesis as low completion rates have been one of the most significant sources of criticism of MOOCs, and the reasons why learners do not complete MOOCs are not yet unequivocally clear. In Figure 1, all factors relevant to this thesis and studied in relation to success based on course completion are shown in green. The second approach to success is based on learner intentions for MOOCs. In the light of the expectancy-value theory (Eccles et al., 1983), learners' individual level beliefs about their own success have been considered in this thesis as learners' intentions regarding a MOOC. These intentions are used as a basis for determining whether learners were successful or not in comparison with how they actually performed in the course. Since intentions themselves are not studied as one of the potential factors influencing learners' success, it is an independent item with different appearance in the figure. As success based on learners' intentions represents an outcome of the course, it is considered as one of the aspects that is affected by expectancies and value. This approach is used due to the nature of MOOCs; course participants can use these courses for different purposes, and therefore, the measure of success for learners is individual. It is studied in this thesis because most of the research on learners' success is based on course completion, but considering learners' individual intentions is significant and requires further studying. In Figure 1, all the factors that are studied in this thesis in relation to learners' individual intentions are presented in blue.

Factors affecting expectancies and value include learners' background characteristics and previous experiences. In the current thesis, their influence is studied on learner's success that is based on their intentions. These factors are relevant as MOOC participants differ in terms of their background and previous experiences, and previous studies have shown conflicting results regarding their impact on course completion.

In the second category, that includes expectancies and value, motivation to enrol on a MOOC represents the positive side of the value. It is important to study motivation to enrol as it helps to understand the benefits and barriers that learners have in advance. In general, learners' motivation affects the outcome of their learning. As most of the research studying motivation that affects learners' success in MOOCs is based on course completion, the current thesis studies the

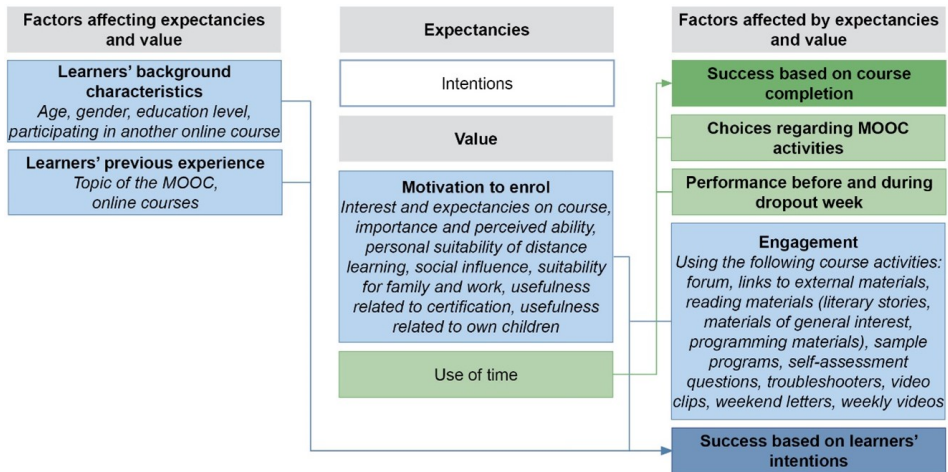


Figure 1: Research model

effect via intentions. The use of time represents the negative side of the value, and it was studied how learners use their time in relation to course completion. Learners' time usage was selected for this study because learners have reported lack of time as one of the main reasons why they are dropping out of MOOCs.

The third category includes factors in expectancy-value theory (Eccles et al., 1983) that have been affected by expectancies and value. The first factor, learners' choices regarding MOOC activities, was studied in relation to course completion. It was selected for this study because not all learners are able to control their own learning in the way that the autonomy to use the course resources and the freedom to create their own learning path in MOOCs would imply. Therefore, learners' success is affected by the manner they use the course activities. The second factor represents learners' performance before and during the week they drop out. Performance is relevant in this thesis to gain insight into how learners interact with the course during different weeks of the course. The third factor is engagement, which was included in this study because it has been one of the central factors affecting learning results in MOOCs. According to the expectancy-value theory (Eccles et al., 1983), engagement has been affected by expectancies and value. However, in the MOOC environment, engagement has influenced learners' success; therefore, the impact of engagement is studied in terms of the individual intentions of learners.

3.2. Context of the study

This subsection describes the courses relevant to this thesis. AP, IP1, and IP2 are three computer programming MOOCs organised by the Institute of Computer Science at the University of Tartu to introduce programming concepts and structures of Python. The courses are held in Estonian. AP, IP1 and IP2 differ in terms of difficulty level. This means that in the case of the courses on the same subject, in

addition to the topics covered, there is also a difference in the course duration and the supporting teaching methods (Luik et al., 2019a). A description of the courses is presented in Table 4.

In these courses, participants were provided with various activities to achieve the learning goals set for the course, to support learners, to share information and to provide entertainment. In the case of AP and IP1, mandatory programming exercises and quizzes were prerequisite activities for completing the course. In addition to mandatory programming exercises, it was also possible to solve additional programming exercises, which helped consolidate new knowledge but had no effect on completing the course. Course completion requirements are described in Table 3. Upon meeting the criteria for completing the course, learners received a certificate.

Among the learning materials, there were three types of reading materials – programming materials, materials of general interest and literary stories. Programming materials were the primary learning materials and included following activities:

- self-assessment questions – to give direct feedback to the acquired knowledge;
- links to additional materials – to provide a more comprehensive overview of the topic;
- sample programs – to give examples of how to use gained theoretical knowledge in practice;
- video clips – to provide alternative explanations for the topic and the solution of sample programs.

To complete the quizzes, learners needed to read, in addition to programming materials, materials of general interest that described some fields related to Information Technology, like self-driving cars (AP) or encryption (IP1). Literary stories were unrelated to any other course activity or course completion, and these stories introduced aspects of programming in literary texts.

For support, programming exercises had troubleshooters that gave learners answers to the questions they may have had when solving a specific programming exercise (Lepp et al., 2018). In addition, participants could contact course organisers via the helpdesk 24/7. The helpdesk could be contacted by email, and the learners received a response within 8 hours. A forum was provided for social purposes. Course organisers sent weekly videos about the situation in the course and weekend letters to remind learners of the upcoming deadlines, encourage participants to ask for help, and give an overview of the week ahead. The activities that were accessible in the Moodle environment, which was the main learning environment of the course, and their sequence of appearance in Moodle, are presented in Figure 2.

In IP2, the basic structure was similar to AP and IP1, but there were no literary stories or helpdesk. In this MOOC, however, programming exercises and quiz

Table 4: Description of the courses

	About Programming (AP)	Introduction to Programming 1 (IP1)	Introduction to Programming 2 (IP2)
Name in Estonian	Programmeerimisest maälähedaselt	Programmeerimise alused	Programmeerimise alused 2
First occurrence	2014	2016	2017
Target group	Learners without previous programming knowledge	Learners without or with little previous programming knowledge	Learners with previous programming knowledge (at least to the extent of the IP1 course)
Duration	4 weeks	8 weeks	8 weeks
Volume	1 ECTS* (26h)	3 ECTS (78h)	3 ECTS (78h)
Examples of covered topics	Variables, data types, conditional, statements, loops, regular expression, functions	Similar topics to AP but covered in more detail. In addition, lists, graphics and user interfaces are introduced	Data structures, nested loops, recursion, two-dimensional data structures
Number of mandatory activities per week	1–2 programming exercises and one quiz	2–4 programming exercises and one quiz	2–4 programming exercises and one quiz (first six weeks), project (last two weeks)
Course completion requirements	Completion of all mandatory programming exercises and quizzes	Completion of all mandatory programming exercises and quizzes	Completion of all mandatory programming exercises, quizzes, and project
Participants across all course runs	Over 12,000	Over 7,100	Over 2,700
Completers across all course runs	Over 7,400 (about 62%)	Over 3,900 (about 55%)	Over 890 (about 33%)

*ECTS – European Credit Transfer and Accumulation System

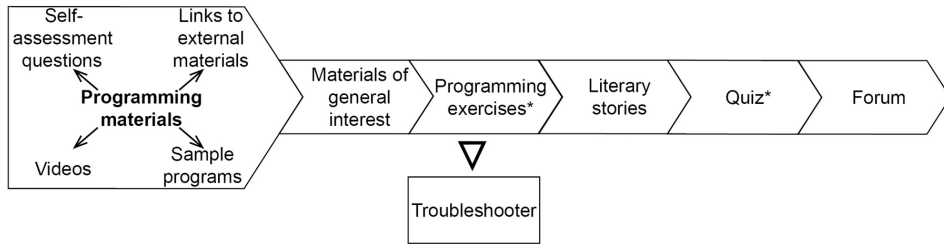


Figure 2: The sequence of the activities in Moodle

Note: * – mandatory activities

were performed in the first six weeks and learners had to prepare a project as a third type of mandatory activities in the last two weeks of the course.

3.3. Sample

This thesis used data from four occurrences of the three previously described CP MOOCs. The relevant courses were two AP courses that ran in the autumn of 2018 (AP18) and the spring of 2019 (AP19), IP1 that took place in the autumn of 2018 and IP2 from the spring of 2019. Table 5 presents the number of enrolled learners and completers for all the courses.

Table 5: Enrollers and completers of all courses

Course	AP18	AP19	IP1	IP2
Enrollers	1,278	1,028	1,552	745
Completers	773 (60.5%)	596 (58%)	828 (53.4%)	253 (34%)

Different samples were used to find answers to the research questions. The courses the data were collected from for each research question are outlined in Table 3. For research questions 1 and 2, data from all these courses (AP18, AP19, IP1, IP2) were obtained. The sample of RQ1 and RQ2 consisted of learners that started the course. This means that they submitted at least one mandatory activity to Moodle. It was not important whether the solution met the activity completion requirements. A description of the sample of RQ1 and RQ2 is presented in Table 6.

The sample of RQ3 consisted of participants from AP19 who completed the pre-questionnaire and answered the question about the probability of completing the course in the range of 0 to 100. Of the 841 participants who completed the pre-questionnaire, the final sample of 834 learners was formed. Table 7 represents the relevant background data of the sample of RQ3.

To answer RQ4 and RQ5, the sample comprised learners from AP18 and AP19 who completed both the pre- and post-questionnaire. There were 1,040 respondents to these questionnaires. The sample of RQ4 consisted of all these participants. In the case of RQ5, out of the course participants who completed both pre- and post-questionnaires, learners were removed from the sample if their sequence

Table 6: Learners' background data for RQ1 and RQ2

Course	AP18	AP19	IP1	IP2
N (% from enrollers)	1,042 (81.5%)	841 (81.8%)	1,375 (88.6%)	605 (81.2%)
Gender (female) (% from N)	570 (54.8%)	459 (54.6%)	697 (50.6%)	282 (46.6%)
Age range	10–70	10–72	10–74	11–74
Average age	32.5 (SD=10.86)	33.25 (SD=11.05)	32.69 (SD=10.29)	33.65 (SD=10.15)

Table 7: Learners' background data for RQ3

N (% from enrollers)	Gender (females) (% from N)	Age range	Average age
834 (81.1%)	457 (54.8%)	10–70	33.4 (SD=11.14)

of activities across all activities in the post-questionnaire did not start with the number 1 or if all activities were marked with the same number. The final sample for RQ5 consisted of 1,003 learners.

The subsample of the qualitative part of the research was the same for both RQ4 and RQ5 and included participants who wrote learning diaries. In summary, there were 79 participants in AP18 and AP19 courses who made more than one entry in their learning diaries. To select learning diaries for the study, 24 out of 79 were picked out as follows: First, all selected learning diaries reflected the entire learning period, i.e. up to the moment of dropout or completion of the course. Second, all five diaries of dropped-out learners were included, as the number of these was significantly smaller. Third, the learning diaries of the course completers were picked out based on learners' characteristics (gender, age, education). Out of the 24 learning diaries selected, ten were written by participants from AP18 and 14 from AP19. The samples for RQ4 and RQ5 are described in Table 8.

3.4. Data collection

This sub-chapter describes the data collection procedures. First, the focus is on quantitative data and then on qualitative. The studies in this thesis have the approval of the Research Ethics Committee of the University of Tartu (341/T-2, 2021–2026) and complied with The European Code of Conduct for Research Integrity (All European Academies, 2017) and guidelines of the Republic of Estonia Data Protection Inspectorate for processing personal data (Andmekaitse Inspektion, 2019). All data were provided to the author of this thesis in an anonymised form, as only the data specialist of the research group of Didactics of Informatics that the author was part of had access to personalised data.

Table 8: Description of the sample for RQ4 and RQ5

	RQ4	RQ5	RQ4 and RQ5
	Respondence of questionnaires		Writers of learning diaries
N (% from enrollers)	1,040 (45.1%)	1,003 (43.5%)	24
Gender (female) (% from N)	584 (56.2%)	571 (56.9%)	14 (58%)
Age	Min: 10 Max: 72 Average: 32.7 (SD=11.05)	Min: 10 Max: 72 Average: 32.9 (SD=11.05)	Min: 16 Max: 58 Average: 35.8 (SD=10.54)

3.4.1. Quantitative data

Questionnaires were chosen to collect quantitative data as these have been used in the past when course completion is relevant to measure success (Lu et al., 2021) and when success is reviewed based on learners' intentions (Henderikx et al., 2017; Reich, 2014). Questionnaires are a quick and direct way to collect data about learners' attitudes and behaviours (Lu et al., 2021). Moreover, depending on the course structure, the log did not allow to collect data on all the activities used in the course and the amount of time learners spent on the activities. The reading materials were located outside of Moodle, with only links to these materials presented in Moodle. Thus, the usage of these activities was not included in log data. Therefore, the questionnaire was also used to collect data about the activities learners performed in the course. The data sources for each research question are presented in Table 3.

The pre-questionnaire was sent to course participants in the first and the post-questionnaire in the last week of the course. In the questionnaires, learners were introduced to the purpose of data collection. It was explained that answering the questionnaires was not anonymous, as the answers to the questionnaires were linked to the learning results. In addition, it was mentioned that the results of data analysis would be presented in a generalised form, and these results would not be associated with any specific person. Learners were asked for permission to use their data, and it was also pointed out that respondents could withdraw their permission at any time.

The data to study the dropout time and performance before the dropout (RQ1 and RQ2) included submission times of each mandatory programming exercise and quiz for all the courses and the project in case of IP2 and whether these activities were completed successfully.

In the case of RQ3, Moodle provided information about how many mandatory activities a participant completed during the course as all mandatory activities were submitted to Moodle. Based on this, the percentage of the completed manda-

tory activities was calculated for every learner. The personal data (age and gender) were taken from the university's Study Information System, through which learners enrolled on the courses. The pre-questionnaire covered other aspects of learners' background data, previous experience, intention to complete the MOOC, engagement and motivation to enrol in the MOOC. Table 9 presents the relevant questions and scales in the pre-questionnaire.

Table 9: Description of instrument for background data, previous experience, and intention

Variable	Question/Statement	Scale
Education level	Please mark the highest level of completed education.	unfinished basic education basic education secondary education higher education master's degree doctoral degree
Previous experience in online courses	Have you participated in fully online courses before?	I have not. I have once. I have multiple times.
Previous experience in programming	Have you studied programming before?	I have never studied programming before. I have only studied independently. I have studied at school, university, or courses (including MOOCs).
Another online course at the same time	Are you taking another fully online course at the same time?	Yes No
Intentions	How likely are you to complete the course (0-100%)?	0-100 (%)

Factors Influencing Enrolment in MOOC (FIEM) scale that is based on the expectancy-value theory (Luik et al., 2019b) was used to measure motivation. Learners could give their evaluations of the aspects affecting enrolment motivation by answering 28 statements that started with the question, "What did motivate you to enrol in the MOOC?" on a 7-point Likert scale. The confirmatory factor analysis conducted by Luik et al. (2019b) showed seven motivational factors formed from the statements that are described in Table 10.

To measure engagement, the respondents were asked to estimate how many of the different course activities they planned to do. The relevant course activities, scale and example statements are presented in Table 11.

Table 10: Description of the motivation factors and examples from the instrument

Factor	Number of items	Examples	Cronbach's alpha
Interest and expectancies on course	8	I get more knowledge from this course. I can participate in a course with excellent instructors.	0.810
Personal suitability of distance learning	4	I can choose the time when I study. Learning, where I do not actually have to meet with other people, suits me.	0.804
Suitability for family and work	2	I can combine learning with work. I can combine learning with family life.	0.876
Importance and perceived ability	6	I need that knowledge in real life. I know that I will do well in this topic.	0.806
Usefulness related to certification	4	I get a certificate from the University. I can show it to the employer as good professional development.	0.739
Social influence	2	My friends think that I would be successful in this course. Members of my family think that I would be successful in this course.	0.743
Usefulness related to own children	2	I would like to help my children in their programming studies. After attending the course, I can understand my children who have programming skills.	0.819

Table 11: Description of instrument for measuring engagement

Course activities	Scale	Example statements
Programming materials Video clips Self-assessment questions Links to external materials Sample programs Materials of general interest Literary stories Weekly videos of the situation in the course Weekend letters Troubleshooters Forum	none about 1/4 about a half about 3/4 all	I'll watch ... of the video clips. I'll visit ... of the links to external materials.

To answer RQ4 and RQ5, both quantitative and qualitative data were collected. In the case of the quantitative data for RQ4, the average number of planned hours that learners intended to spend on the course per week was gathered with the pre-questionnaire. The average number of hours per week learners spent studying and ratings of time-related factors (e.g. I would have liked to devote more time to the course.) were collected with a post-questionnaire. Ratings were given on a 7-point Likert scale. For the comments on using time, the AP19 post-questionnaire had an open-ended question.

For RQ5, with a post-questionnaire, quantitative data were collected on the sequence in which learners usually did the different activities of the course when learning a new topic. The questions were about nine course activities that were accessible in Moodle and presented in Figure 2 (except for sample programs and links to external materials). The tenth activity was searching for additional materials outside the course environment.

In the post-questionnaire, the respondents were asked to mark with number 1 the first activity they usually engaged with, the second activity with the number 2, etc. If a learner did not do a particular activity during the course, it was to be marked with 0. If several activities were used simultaneously, these activities were to be marked with the same number. If a sequence was not marked as consecutive, the answers were modified accordingly before data analysis. With an open-ended question, learners could leave comments about the sequence of activities.

3.4.2. Qualitative data

Qualitative data for RQ4 and RQ5 were gathered with learning diaries. This instrument was chosen as it enables the collection of data about the learning experience, with chronological entries by learners in text-based learning diaries. Moreover, these are learning tools that help course participants reflect on and

evaluate their learning process (Debbag & Fidan, 2020). Learners were invited to specify in Moodle the activities they looked at in the course and the order in which they engaged with the learning materials or solved the exercises. From a learning time perspective, course organisers were interested in knowing at what time participants attended the course and how long they spent on the course at a time. Learners were also asked to write about the thoughts, opinions, and emotions the learning evokes, and what they felt hinders and/or facilitates learning in this course. The learning diaries were available only to the course organisers and not accessible to other course participants. Learners' names were replaced by pseudonyms to ensure anonymity.

3.5. Data analysis

This sub-chapter provides an overview of the data analysis process. As this thesis uses quantitative dominant mixed methods research, the focus is on quantitative data and following this, the analysis of qualitative data is described.

3.5.1. Quantitative data

Quantitative data were analysed with the statistical software platform IBM SPSS Statistics. To find the periods with the highest dropout (RQ1), first, each learner was assigned a status for each course week. The learner was considered active up to (and including) the week when the learner last submitted some mandatory activities to Moodle. A learner was considered inactive starting from the week when the learner did not have any submissions of mandatory activities in the current and in the following weeks. Second, the statuses of learners were compared between different weeks. It was performed with McNemar's test as, according to Field (2009) this test should be used when there are two dichotomous variables and changes in scores are looked at; in the current case, the changes occurred in learners' status between the weeks. Third, the number of dropouts in a week was found so that the week in which the learner was last active was considered the week of dropping out. It should be noted that in the case of IP2, the number of dropouts in week seven represents both weeks 7 and 8, as learners prepared a project in these two weeks, and there were no other mandatory course activities to submit.

To find how learners performed until the end of the dropout week (RQ2), they were divided into groups. It was done based on if and how successfully they submitted the mandatory course activities during the dropout week and in the preceding weeks. Successful completion of a learning week was registered if all relevant mandatory activities for this week were submitted and met the completion criteria. A learning week was not completed if some or all mandatory activities were not submitted or submitted activities did not meet the completion criteria. The different groups of dropouts are described below:

- Completed current and all previous weeks – non-completers who completed all mandatory activities in the dropout week and in all previous weeks;
- Completed current week, but not previous weeks – dropouts who completed all mandatory activities in the week of dropping out, but did not complete activities in at least one of the previous weeks;
- Completed previous weeks, but not the current week – non-completers who completed all mandatory activities in each previous week, but did not complete the dropout week;
- Did not complete current and at least one of the previous weeks – dropouts who did not complete the mandatory activities in the week of dropping out and in at least one of the previous weeks;
- All weeks not completed – non-completers who did not complete mandatory activities in the dropout week and in any of the previous weeks.

Using descriptive statistics, the number of course participants in each group for all the weeks of the course was found. Next, the percentage distribution of learners belonging to the groups was compared for each week with Z-test to find the largest group.

For RQ3, the factors affecting learners' success were found using a decision tree algorithm. It was chosen because it is considered a capable tool (Song & Lu, 2015), and it outperformed other methods when factors affecting learners' dropout were analysed (Gupta & Sabitha, 2019). A decision tree is a non-parametric approach that has no distributional assumptions. This method divides the independent variables into significant subgroups and makes the complex relationships between the independent and dependent variables easier to understand and interpret (Song & Lu, 2015). The tree-like structure of the decision tree contains the root, leaf, and non-leaf nodes (Lee et al., 2022).

In the created model, learners' background data, their previous experience with programming and online learning, the estimates of engaging with the 11 different course activities and the mean scores of the seven motivation factors were used as independent variables. The dependent variable was learners' success. It was the difference between the percentage of completed mandatory activities and the percentage that learners described as their intentions to complete the course. Success was calculated based on the approach recommended by Henderikx et al. (2017). A learner was categorised as successful when the percentage of completed mandatory activities was equal to or higher than the percentage of the intentions and unsuccessful when the percentage of mandatory activities was lower than the percentage of intentions.

The decision tree was created with the CHAID (Chi-Squared Automatic Interaction Detection) growing method, which uses Chi-square test (Song & Lu, 2015) with Bonferroni correction (Antipov & Pokryshevskaya, 2010) when choosing the input variable. In practice, ten folds are frequently used (Berrar, 2018), and therefore ten were also selected for this thesis. This means that, during the creation

of a decision tree, the data is divided into ten groups, and ten decision trees are created based on these groups. Each time, 10% of the data is left out as test data. The accuracy of the final decision tree is formed by the average of the accuracies of the ten trees created. Cross-validation was used to estimate the true prediction error of the model. It was selected as it is the most used method for evaluation (Berrar, 2018).

To analyse the quantitative data for RQ4 and RQ5, descriptive statistics (percentages, frequencies) were applied to the estimates about the amount of planned and used time and time-related statements (RQ4). In the same way, it was determined how many learners performed certain course activities and for how many learners this activity was the first or last activity (RQ5). Comparisons were performed with several comparison tests. Wilcoxon signed-rank test was chosen to compare the estimates of planned and used time as there were two dependent samples, and the data were on an ordinal scale. To compare completers and non-completers, due to the two independent samples and ordinal scale data, Mann-Whitney U-test was used to compare the responses to time-related statements and ratings of the sequence of the activities. For comparing percentages of how many different course activities were performed, a Chi-square test was used.

3.5.2. Qualitative data

This thesis used quantitative dominant mixed methods research. Therefore, to add learners' direct perspective to the study, the qualitative data analysis was based on getting an overview of how learners perceive the use of their time and the factors affecting it and how they explain their choice of course activities. With examples of programming code, links and pictures included, the total length of all the learning diaries relevant to this thesis was 74 pages, in Times New Roman font and with 1.5 line spacing. The number of words in the learning diaries ranged from 275 to 3,039. The analysis was conducted in the QCMap program, which allows data to be stored, organised and analysed.

Inductive thematic content analysis, including manifest content, was used to analyse data from learning diaries for RQ4 and RQ5. Inductive content analysis is suitable when the knowledge from previous studies about a topic is fragmented and includes open coding, the creation of categories and abstraction (Elo & Kynäs, 2008). Initially, two steps were performed as described by Flick (2009). First, meaningful units (a single word or a short phrase) from the texts were segmented to attach codes to them. Second, the detected codes were grouped into categories based on the phenomenon found in the data and considering its significance for the research question. During abstraction, categories describing similar events were grouped together to form the main categories (Elo & Kyngäs, 2008).

The author of this thesis independently coded all learning diaries. The coding process was repeated multiple times. In the process, the codes were supplemented, repetitive codes were removed, and the wording of the codes was changed. Su-

pervisor Piret Luik co-coded the topics of learners' perception of their time usage and reported sequence of course activities in relation with RQ4 and RQ5, respectively. Coding decisions were discussed until consensus was reached. The main differences were in the wording of the codes and the lengths of meaningful units.

In the case of RQ4, the qualitative part of the research was more dominant, and the quantitative results complemented qualitative results. All statements in the learning diaries in which learners wrote about time were considered time-related segments. For example, the segments included phrases like 'more time', 'not enough time' and 'planned time'. Three main categories emerged: (1) usage of time, (2) time-related factors contributing to learning, and (3) time-related factors which hinder learning.

Regarding RQ5 and qualitative data, the segments about course activities were counted based on when learners wrote about the ten course activities. Three main categories were formed about how learners explain their choice of course activities during learning: (1) reasons for performing an activity, (2) reasons for not performing an activity, and (3) reasons for the selected sequence. Another three main categories emerged for the reasons why learners changed the sequence: (1) problems with understanding the topic, (2) saving time, and (3) activity discontinued.

4. FINDINGS

This chapter presents the main findings according to the research questions posed in this thesis. Sub-chapter 4.1 focuses on the periods when dropout is highest. Sub-chapter 4.2 provides an overview of learners' performance before dropping out. Sub-chapter 4.3 describes the factors that affect learners' success.

4.1. Periods with the highest dropout rate

This sub-chapter answers RQ1 and is based on Publication I. First, the focus is on two occurrences of the four-week course "About Programming", AP18 and AP19. Next, the results for eight-week courses IP1 and IP2 are described. The highest number of learners dropped out of AP18 and AP19 in the first and second weeks. For 83 (8%) and 95 (9.1%) learners in AP18, the first or second week was the last week of the course, respectively. In the case of AP19, last mandatory activities in the course were submitted by 92 (10.9%) learners in the first week and by 74 (8.8%) in the second week. The weekly percentage of dropped out learners from learners that started AP18 and AP19 is shown in Figure 3.

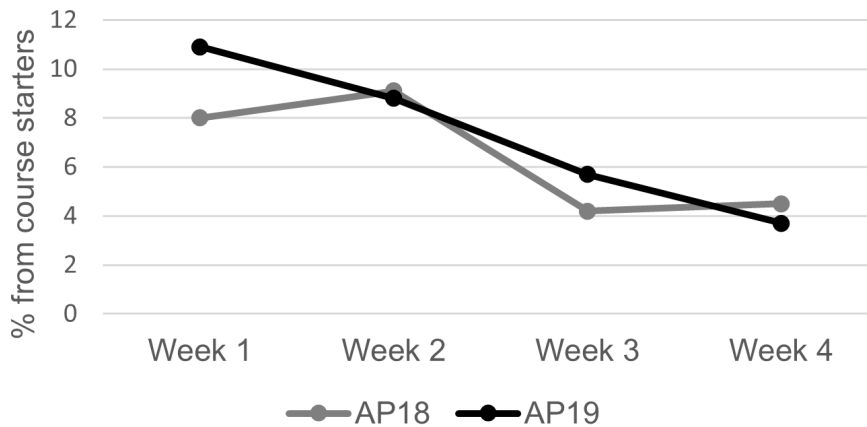


Figure 3: Last week of activities in AP18 and AP19

In the case of both AP courses, when the number of dropouts in different weeks was compared, no statistically significant difference was found between the first and second week ($p > 0.05$). However, both the first and second weeks had statistically significant differences to the third and fourth weeks (in the case of AP18, chi-squared value was between 9.42 and 17.99; for AP19 chi-squared value was between 5.12 and 29.27, $p < 0.05$).

Figure 4 shows weekly percentages of learners who dropped out of IP1 and IP2. Comparing the number of dropouts by week in IP1 showed that more learners dropped out at the beginning of the course compared to the end of the course.

In the first and second weeks, the number of dropouts was 90 (6.5%) and 110 (8%), respectively. Statistically significant differences were found between the first and second weeks and the sixth, seventh and eighth weeks (chi-squared value was between 6.97 and 46.04, $p < 0.05$). The second and third (chi-squared=4.76, $p < 0.05$), fifth and sixth (chi-squared=4.14, $p < 0.05$) and sixth and seventh (chi-squared=5.32, $p < 0.05$) weeks also differed statistically significantly.

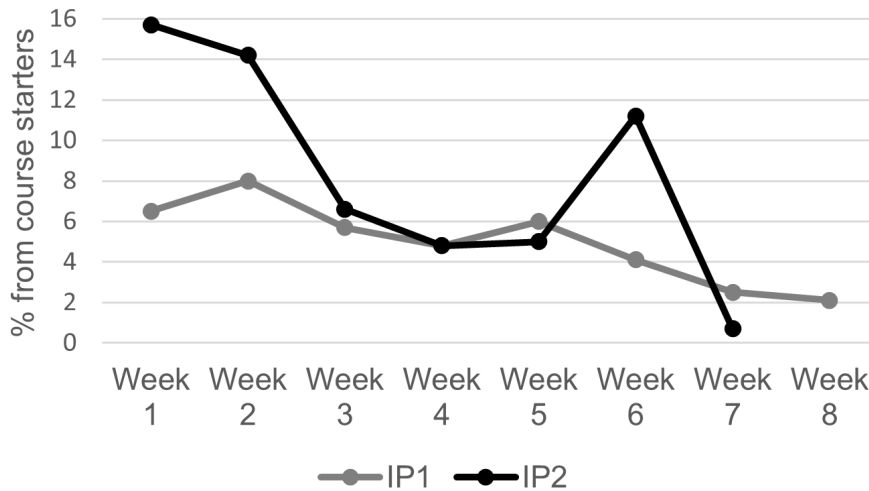


Figure 4: Last week of activities in IP1 and IP2

Comparing the number of learners who did their last activity in the corresponding week in IP2 showed that more learners left the course in the first and second weeks than in weeks three, four, five and seven (chi-squared value was between 16.07 and 81.82, $p < 0.05$). The number of dropouts in week one was 95 (15.7%), and in week two, 86 (14.2%). In week six, 68 (11.2%) learners left the course, which is more than in weeks five (chi-squared=14.89, $p < 0.05$) and seven (chi-squared=55.13, $p < 0.05$). The dropout was lowest in week seven which represents the last two weeks of the course when learners prepared their project. The number of dropped out learners was 4 (0.7%) in these weeks (chi-squared value was between 17.46 and 81.19, $p < 0.05$).

4.2. Performance during dropout week and previous weeks

The current sub-chapter relies on Publication I and answers RQ2. Table 12 represents the groups learners were divided into, based on the completion of the course activities during the week of dropping out and in the weeks preceding it in AP18 and AP19.

For AP18 and AP19, most learners who dropped out in the first week completed all the activities for that week and then left the course. In the case of dropouts in the second week, the largest group includes learners who completed

Table 12: Completion of different course weeks by dropped-out learners in AP18 and AP19

Course	Week	Number of dropouts	Completed current and all previous weeks	Completed current week, but not previous weeks	Completed previous weeks, but not current week	Did not complete current and at least one of the previous weeks	All weeks not completed
AP18	1	83	56 (67.5%)*	N/A	N/A	N/A	27 (32.5%)
	2	95	55 (57.9%)*	7 (7.4%)	23 (24.2%)	N/A	10 (10.5%)
	3	44	4 (9.1%)	0 (0.0%)	29 (65.9%)*	6 (13.6%)	5 (11.4%)
	4	47	N/A	7 (14.9%)	8 (17.1%)	16 (34.0%)	16 (34.0%)
AP19	1	92	55 (59.8%)*	N/A	N/A	N/A	37 (40.2%)
	2	74	47 (63.4%)*	1 (1.4%)	17 (23.0%)	N/A	9 (12.2%)
	3	48	11 (22.9%)	1 (2.1%)	23 (47.9%)*	7 (14.6%)	6 (12.5%)
	4	31	N/A	6 (19.4%)	3 (9.7%)	11 (35.5%)	11 (35.5%)

Notes: * – largest group(s) of dropped-out learners in the respective week (p<0.05)

N/A – “not applicable”

all the mandatory activities of the first two weeks without submitting any activities in the third. In the third week, most dropouts completed all activities in the first two weeks but did not complete the current week. There were no differences between the groups in the last week of the course ($p>0.05$).

During weeks two, three and five of IP1, most dropouts had completed all the mandatory activities in previous weeks but were unable to complete activities in these weeks. During other weeks there were no differences between groups, or multiple groups emerged. Table 13 represents the groups of learners for IP1 and IP2.

At the beginning of IP2, over two-thirds of learners left the course without completing the first week. In weeks two and three, most dropouts had completed the mandatory activities in the previous weeks but failed to complete the current week. There were no differences between groups in weeks four and five. In the sixth week, over half of the dropouts had completed all six weeks before leaving the course.

4.3. The factors affecting learners' success based on their intentions

This sub-chapter provides an overview of the findings regarding the various factors that may influence learners' success in MOOCs and provides answers to RQ3-RQ5. When quotes from learners are used to present the qualitative results, a description of the learner is provided that includes the learner's pseudonym, the course the learner participated in, and whether the learner is a completer (C) or a non-completer (NOC).

4.3.1. Learners' background, engagement, and motivation

This sub-chapter answers RQ3 and bases on the Publication II. RQ3 was answered using data from AP19. The decision tree model using the CHAID growing method formed a tree with 11 nodes, 6 of which were terminal nodes. The depth of the tree was 3. Of the independent variables, the following five were predictors: educational level, previous experience with programming and online courses, intention to visit the referred external links, and usefulness related to certification. The formed decision tree is illustrated in Figure 5.

Node 0 shows that 68.5% of the learners performed as they intended or better. The second level of the three (nodes 1 and 2) indicates that educational level was the most effective variable for predicting success. Of the participants who had obtained a bachelor's degree or lower, 64.8% were successful, and of the learners with higher than a bachelor's degree, 76.4% managed to fulfil their intentions or do more.

Node 1 was divided into two nodes based on the predictor 'intention to visit the referred external materials'. Node 3 represents the learners who planned to

Table 13: Completion of different course weeks by dropped-out learners in IP1 and IP2

Course	Week	Number of dropouts	Completed current and all previous weeks	Completed current week, but not previous weeks	Completed previous weeks, but not current week	Did not complete current and at least one of the previous weeks	All weeks not completed
IP1	1	90	42 (46.7%)	N/A	N/A	N/A	48 (53.3%)
	2	110	24 (21.8%)	0 (0.0%)	81 (73.6%)*	N/A	5 (4.6%)
	3	79	21 (26.6%)	1 (1.3%)	44 (55.7%)*	11 (13.9%)	2 (2.5%)
	4	66	25 (37.9%)*	6 (9.1%)	24 (36.4%)*	10 (15.1%)	1 (1.5%)
	5	82	22 (26.8%)	2 (4.4%)	37 (45.1%)*	20 (24.4%)	1 (1.2%)
	6	57	20 (35.1%)	1 (1.8%)	21 (36.8%)	14 (24.5%)	1 (1.8%)
	7	34	7 (20.6%)	0 (0.0%)	15 (44.1%)	12 (35.3%)	0 (0.0%)
	8	29	N/A	0 (0.0%)	13 (44.8%)*	13 (44.8%)*	3 (10.4%)
IP2	1	95	31 (32.6%)	N/A	N/A	N/A	64 (67.4%)*
	2	86	8 (9.3%)	0 (0.0%)	72 (83.7%)*	N/A	6 (7.0%)
	3	40	7 (17.5%)	2 (5.0%)	20 (50.0%)*	9 (22.5%)	2 (5.0%)
	4	29	13 (44.8%)	0 (0.0%)	7 (24.1%)	8 (27.7%)	1 (3.4%)
	5	30	7 (23.3%)	2 (6.7%)	14 (46.7%)	6 (20.0%)	1 (3.3%)
	6	68	38 (55.90)	0 (0.0%)	17 (25.0%)	12 (17.6%)	1 (1.5%)
	7	4	N/A	4 (100%)	0 (0.0%)	0 (0.0%)	0 (0.0%)

Notes: * – largest group(s) of dropped-out learners in the respective week (p<0.05)

N/A – “not applicable”

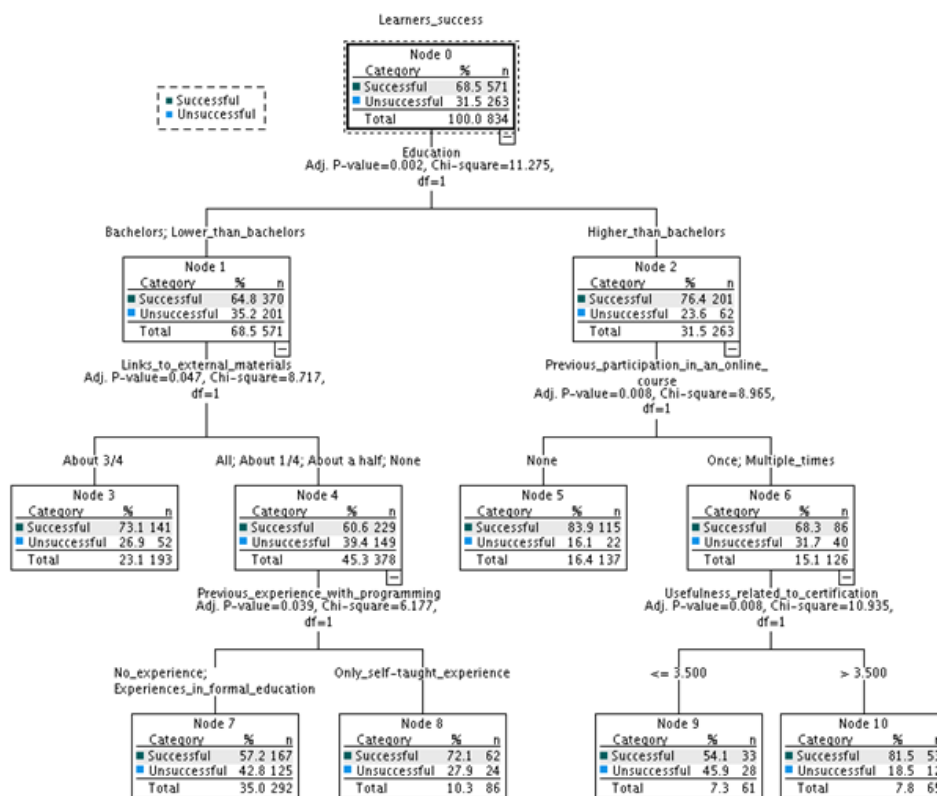


Figure 5: Results of the decision tree analysis using the CHAID growing method

visit about 3/4 of the links in learning materials. Node 4 corresponds to the participants whose intention was to access either less or more than 3/4 of the referred links. Out of these participants, 73.1% and 60.6% were successful, respectively. The next predictor, for participants with lower education who intended to use either more or less than 3/4 of the external materials, is previous experience with programming. Node 7 indicates that 57.2% of the learners who had no previous programming experience or had learned programming as part of their formal education performed as they initially intended or better. Of the participants with only self-taught programming experience, 72.1% were successful.

With respect to the input variable of previous experience with online courses, node 2 splits into two nodes (nodes 5 and 6). Among the participants with no previous experience with online courses, 83.9% were successful. Of the learners who had previously participated in online courses, 68.3% were able to perform as they intended or better. The predictor of usefulness related to certification divided node 6 into two additional nodes (nodes 9 and 10). Among the learners who had a degree higher than a bachelor's, had previous experience with online courses, and with 3.5 or lower as the average rating for the current motivation factor, 54% managed to fulfil their intentions or do more. Out of the learners with an average rating greater than 3.5, the proportion of successful learners was 81.5%.

Table 14 includes the risk error estimates of the decision tree model. Resubstitution error shows the classifier adaption to the training data (Berrar, 2018). The value of resubstitution error was 31.5% for the current CHAID model. The cross-validation error, the true prediction error (Berrar, 2018), was 32.5%.

Table 14: Risk estimates of the classifier

	Estimate	Standard error
Resubstitution	0.315	0.016
Cross-validation	0.325	0.016

4.3.2. Perception of time usage and the factors affecting it

The following sub-chapter gives an overview of the most relevant results regarding RQ4. More detailed results can be found in Publication III. To find answer to RQ4, both quantitative and qualitative data from the courses AP8 and AP19 were used.

Usage of time. In their learning diaries, participants wrote about setting time-related learning goals for the ongoing week. They scheduled their learning time and responded to changes that forced them to change the plans. A learner wrote, “*I was planning to start looking at things for the second week on Wednesday, but since today (Tuesday) was also a chance to lock myself in my room, I’ll start today ...*” (Aurora, AP19, NOC). Participants had to change their personal plans if learning took longer than expected. However, when the planned learning activities were completed early, they continued learning and could do more than planned. While planning their time, learners analysed their opportunities and abilities for learning. In addition, a pattern evolved of how participants distributed their time for activities for one week. One learner explained her learning pattern as follows:

I generally engaged in the course three days a week for an average of 2 hours or less at a time. Usually, I did the first part of the two parts on the first day, the second part on the second time, and the third time, I did the quizzes and submitted the exercises. (Matilda, AP18, C)

Based on learning diaries, both completers and non-completers had a plan on how to use time on the course. Time was planned within one week, and they analysed their progress in the course and understood if they needed to make changes. Only completers wrote that they made the changes or did more than they had initially planned.

Learners started the activities of a new week on Fridays when new materials were opened or at the end of the current week on the weekend when the deadline was approaching. Learning started early when learners were enthusiastic about continuing the course or the week’s topic seemed difficult. One participant stated, “*As soon as I saw the topics of the week, I set out to start learning and solving*

assignments as early as possible.” (Paul, AP18, C). Even when learners planned to study on weekdays, they had difficulty finding the time.

According to the pre-questionnaires, learners mainly intended to engage in learning activities for 4 to 6 hours a week. However, based on the post-questionnaires, the actual time spent was mostly shorter, from 2 to 4 hours. The answers to the questionnaires about the amount of planned and used time are described in Table 15. A comparison of planned and used time conducted with Wilcoxon signed-rank test showed that participants planned to spend more time than they did ($Z=-13.543$, $p<0.05$). Like all learners, completers also planned to spend more time than they spent ($Z=-13.487$, $p<0.05$). No statistically significant difference occurred in the case of dropouts ($p>0.05$). When the planned and used time was compared between completers and dropouts, there was no statistically significant difference ($p>0.05$).

Table 15: Amount of planned and used time based on questionnaires

Use of time per week	Planned time		Used time	
	Number of learners	Percentage	Number of learners	Percentage
less than 2 hours	20	1.9	93	8.9
from 2 to 4 hours	153	14.7	347	33.4
from 4 to 6 hours	437	42.0	352	33.8
from 6 to 8 hours	291	28.0	156	15.0
from 8 to 10 hours	101	9.7	68	6.5
more than 10 hours	38	3.7	24	2.3
<i>Total</i>	<i>1,040</i>	<i>100.0</i>	<i>1,040</i>	<i>100.0</i>

In their learning diaries, participants wrote about or marked the days they engaged with the learning activities. Five learners spent up to 2 days, four 3 to 4, and four more than 5 days a week. Based on the learning diaries, it cannot be concluded that there is a difference between completers and dropouts in the number of days they used for learning in a week. The participants who wrote about the length of the learning sessions mostly engaged with the course activities for more than 2 and up to 4 hours in a row. Participants spent more consecutive time on the course when they did not manage to complete the programming exercises successfully or when all necessary activities had to be completed due to an approaching deadline. One participant described the time spent solving an exercise as follows:

Additional exercise Family income. Figuring out, messing around and trying. It seems that I got it done, but Moodle suggested thinking again. I have to be there at a certain time today... Getting dressed... Wait, there was one more thought... doesn't work, put on shoes.... hmm... next thought... doesn't work... put on a jacket and.... aaaa, I guess I know now.... I'm already late, but I will try

again; it won't take long....it works!!! Moodle allowed leaving home.
(William, AP18, C)

On the positive side, learning sessions were longer when the topic was interesting, additional functionality was added to the programming exercise solution, or learners were motivated by their previous success and wanted to continue learning.

The sessions were shorter if learners understood the new topic based on the reading materials, were not tired or studied in an uncomfortable environment such as a bus. Learning was started even when there were 20–30 minutes of spare time. However, this led to a situation where learners could not focus enough on the learning activities and had to start again with the material they had already worked on. One learner wrote the following about his experience:

When I see that I can take at least 20–30 minutes to study, I start to delve into the topic. /.../ I hardly manage to open the lecture materials and delve into them when there is a "force majeure" interruption (children, etc.), and later, I start again from "zero". (Paul, AP18, C)

The learning diaries revealed that if there was not enough time for all the learning activities, the activities that were not mandatory were skipped, like the forum and additional programming exercises. Based on the answer to the open-ended question in the post-questionnaire, learners gave up on additional programming exercises after they had worked on these from 30 minutes to 9 hours. However, learners planned to complete the skipped additional programming exercises after the end of the course.

Learners tried to solve programming exercises for 1–2 hours before they needed support and contacted the helpdesk. However, solving the exercise continued after the helpdesk had been contacted. For instance, *"I wrote again to the helpdesk, but I also tried to experiment myself; how difficult can it be?"* (Olivia, AP18, C). Based on the answers to the open-ended question in the post-questionnaire, the mandatory programming exercise that took the longest to solve, about 24 hours, dealt with the topic of functions.

Time-related factors that contribute to or hinder learning. In the post-questionnaire, learners were asked to assess different time-related statements that are presented in Table 16. Two-thirds of the respondents would have wanted to spend more time on the MOOC. For most of the participants (89.8%), their family members were understanding about the time they spent on the course. Only 28 (2.7%) of the respondents felt that they experienced conflicts at home or at work due to spending time on the MOOC. The majority of the learners (86.0%) did not have to miss important things or put them on hold because of the course. There was almost equal distribution between the respondents who felt that they had (42.5%) or did not have (45.9%) unexpected urgent responsibilities while participating in the MOOC.

Table 16: Time-related factors from post-questionnaires

	Disagreed	Neutral	Agreed
Would have liked to have devoted more time to the course	209 (20.1%)	130 (12.5%)	701 (67.4%)
I had difficulties finding time for the course	486 (46.7%)	144 (13.8%)	410 (39.4%)
Because of the course, I missed important things or put them on hold	895 (86.0%)	60 (5.8%)	85 (8.1%)
Due to the time spent on the course, I encountered conflicts at home / at work	997 (95.8%)	15 (1.4%)	28 (2.7%)
There were unexpected urgent responsibilities during the course	477 (45.9%)	121 (11.6%)	442 (42.5%)
Family members were understanding of the time spent on the course	42 (4.1%)	64 (6.2%)	934 (89.8%)

When the answers of completers and dropouts were compared, two statements with a statistically significant difference were found. Dropouts rated higher the statements ‘I had difficulties finding time for the course’ ($U=8642.5$, $p<0.05$) and ‘Due to the time spent on the course, I encountered conflicts at home / at work’ ($U=9821.5$, $p<0.05$).

According to the learning diaries, family, friends, work, weather, course materials, and tools could be both contributing and hindering factors to the use of time. On the one hand, even if participants had scheduled time for learning, emerging family-related activities were prioritised over the MOOC. One participant described this situation as follows:

./../ The week flew by, and there was no time left in the working week. I thought, on Friday when everything is quiet. ./../ [S]ister's family came from Tallinn, and there went the Friday night and Saturday.
(Mary, AP19, C)

There was also no time to do course activities when the time was spent meeting friends. Long working hours made it difficult to find time for learning, or learners were too tired to engage in the learning activities. On the other hand, learners got help from family members, friends and colleagues who knew how to program. This only applied to completers. Non-completers did not write in the learning diaries about receiving extracurricular support. Also, in connection with work, learners used working hours for learning. A participant wrote, “*I started yesterday ./../ during the working day (I work in a ./../ laboratory, and there are often so-called waiting breaks between experiments).*” (Ruby, AP19, C).

The forum and helpdesk were pointed out as tools to get quick help. One learner described her experience as, “*I gathered my courage and sent my piece to prog@ut.ee. ./../ [T]he answer came quickly and was pleasantly positive.*” (Olivia, AP18, C). Time was saved with the printed reading materials, which were

used to take notes and look for information when doing programming exercises and quizzes. Conversely, it was mentioned that using a troubleshooter took a long time. It was even considered a waste of time by some of the respondents.

If the weather was nice during the spring course, learners were drawn to outdoor activities, like gardening, and it was difficult for them to concentrate on learning. One participant wrote, “[B]eautiful weather steals the last desire to spend 3+ hours at the computer and niggle.” (Mary, AP19, C). However, during bad weather, learners engaged in course activities.

As hindering factors to their time use, learners mentioned technical problems related to poor internet connection and Thonny, which was the tool learners wrote their Python code in. In addition, vacation and health conditions affected learners’ use of time for learning. During vacation, it was challenging to find the time to learn, and when learners were ill, learning activities took longer or pending activities piled up.

4.3.3. Description of the sequence of course activities and learners’ justification of their preference

To answer RQ5, both quantitative and qualitative data from AP18 and AP19 were used. This sub-chapter reports the main results of RQ5. More detailed results were provided in Publication IV.

The sequence of course activities. In the post-questionnaire, learners marked which course activities they performed and in which order. All course activities were used by 362 (36.1%) participants. One learner conducted only programming exercises and quizzes, which were mandatory activities. Three participants took part in three activities. In addition to programming exercises and quizzes, one searched for additional materials, used the forum, and answered self-assessment questions. Table 17 describes how many learners performed different course activities and for how many participants a specific activity was the first or last.

Reading programming materials was the first activity in a learning week for most participants, as 891 (91.5%) learners who read the programming materials performed it first. Figure 6 illustrates the sequence in which learners participated in the course activities after reading the programming materials.

Watching videos and answering self-assessment questions were performed at the beginning of the sequence of activities. Only 20 (2.0%) learners did not use self-assessment questions. Other reading materials were completed mostly after the programming materials, and the literary stories were usually read last. These were not mandatory and were not related to any other course activity. Still, only 146 (14.6%) learners did not read them. Participants mainly started solving the mandatory programming exercises after finishing the reading materials. There were 28 (2.8%) learners who solved programming exercises as the first activity of the week. According to the learning diaries, if learners started with program-

Table 17: First and last activities based on post-questionnaire (N=1,003)

	Learners who performed the activity	First activity (% of those who did it)	Last activity (% of those who did it)
Solving the mandatory programming exercises	1,000 (99.7%)	28 (2.8%)	24 (2.4%)
Taking the quiz	999 (99.6%)	11 (1.1%)	345 (34.5%)
Answering self-assessment questions	983 (98.0%)	42 (4.3%)	18 (1.8%)
Reading programming materials	974 (97.1%)	891 (91.5%)	15 (1.5%)
Reading materials of general interest	973 (97.0%)	16 (1.6%)	33 (3.4%)
Watching videos	892 (88.9%)	52 (5.8%)	56 (6.3%)
Reading literary stories	857 (85.4%)	20 (2.3%)	113 (13.2%)
Searching for additional materials	743 (74.1%)	13 (1.7%)	127 (17.1%)
Using troubleshooters	739 (73.7%)	9 (1.2%)	109 (14.8%)
Using the forum	651 (64.9%)	13 (2.0%)	282 (43.3%)

ming exercises before reading the programming materials, they wanted to get acquainted with the exercise first and then solve the exercise and read the materials simultaneously. Based on the post-questionnaire, 739 (73.7%) learners used troubleshooters, mostly while solving the programming exercises. In the learning diaries, learners wrote that they used troubleshooters before programming exercises if they wanted to prepare themselves for solving the exercises by looking at what information the troubleshooters contained in case they needed help when performing the exercises. For example, one participant stated, “*The troubleshooter of the II exercise has been clicked through, so it is known what to expect if it is needed in the future.*” (Sophia, AP18, C).

According to the post-questionnaire, the quiz was usually completed in the second half of the sequence. It was written in the learning diaries that the learning week was started with the quiz if learners wanted to make sure that they were already familiar with the topic. The forum was used before programming exercises if learners wanted to familiarise themselves with problems encountered by other learners, to avoid similar issues. However, based on the post-questionnaire, the forum was mainly used as one of the last activities. It was the last activity for 282

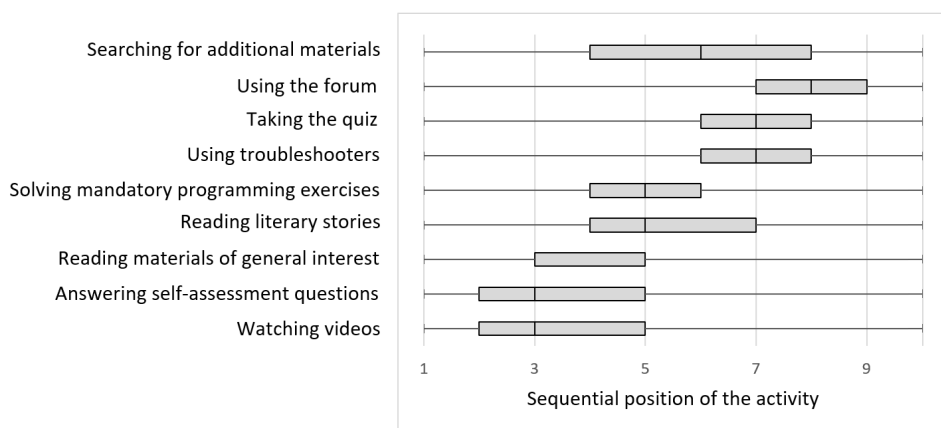


Figure 6: The sequence of activities, based on the post-questionnaire

(43.3%) learners who had used the forum. Additional materials were searched at different phases of the learning week after reading programming materials, and 260 (25.9%) learners did not look for additional materials.

Comparing the position of different course activities in the sequence of activities between completers and dropouts showed that answering the self-assessment questions was later in the sequence for dropouts ($U=7305.0$, $p<0.05$). In the case of other course activities, no statistically significant difference was found ($p>0.05$). Completers and dropouts were also compared in relation to performing or not performing certain activities. Based on a Chi-squared test, a statistically significant difference existed for solving programming exercises and answering self-assessment questions. However, further analysis was needed for both activities with a Fisher's exact test as the expected frequency was less than 5. As a result, no differences were found ($p>0.05$).

Reasons to use or skip activities. In their learning diaries, learners wrote about why they used or skipped different activities. Self-assessment questions were used as these helped to understand the subject. Videos were not watched when learners were able to obtain the needed knowledge from programming materials, experienced technical difficulties, or when having young children nearby made watching the videos inconvenient. One participant stated, "[S]ince it is difficult to watch videos on a computer with a young child, I ignored all the video material." (Olivia, AP18, C). The content of quiz questions, interesting topics and helpful information for the future were the reasons why learners read materials of general interest. These materials were skipped if the topic was not attractive. Learners read literary stories because they were amusing but avoided them when they seemed like a waste of time or felt strange. Discontinuing the use of an activity until the end of the current course was also one of the reasons for changing the sequence of activities. For example, learners did not understand the necessity of the literary stories and stopped reading these after the first week. Activities

were also skipped to save time, which was the second reason learners changed the sequence of activities.

Participants searched the forum for new ideas and alternative solutions for the programming exercises. After completing the exercises, the forum was used to help other learners. The forum was avoided when participants wanted to save time, did not need help with programming exercises, found the forum irrelevant or forgot to use it. Learners searched for additional materials if the subject was not understood from the programming materials, a different explanation was needed, or they wanted to read more about the topic in addition to the course materials.

Help was sought from various other activities when there were problems with solving the mandatory activities. In the case of programming exercises, learners used programming materials, troubleshooters, the forum, videos, self-assessment questions and additional materials. As stated in a learning diary, *"I also used the help of the troubleshooter for the first time, and thanks to the example of summation, I was able to solve the problem. I also looked for help from others' forum posts."* (Rosie, AP19, C). Participants preferred to search for additional materials instead of using troubleshooters when they needed to recall something quickly about a programming exercise. Troubleshooters and searching for additional materials were skipped when no other help was needed. When learners wanted to challenge themselves while solving the programming exercises, they did not use troubleshooters and the forum. One participant wrote, *"I also follow the forum, but I do not really delve into the discussion before solving the exercises. I try to avoid seeing suggestions for solving the exercise."* (Paul, AP18, C). Needing help was also the third reasons learners needed to change their sequence of activities. In addition to the various course activities that learners had to start using to get help, participants used the reading materials to search for the necessary information at the same time as solving the exercises or the quiz. One learner wrote, *"I changed the way I study. Previously, I read the theory section before, and then I went on to do the exercises. Now I decided to do the opposite."* (Olivia, AP18, C). Different course activities were used at the same time also to reduce the time spent on learning.

Learners also wrote that they wanted to solve programming exercises only based on the knowledge they gained from programming materials. To do so, they avoided troubleshooters and the forum and did not search for additional materials. Problems with solving the quiz occurred if participants had skipped the learning materials related to the questions of the quiz. In these situations, in parallel with the quiz, learners used text resources, videos and additional materials. For example, one participant described her situation as follows: *"While doing the quiz, I encountered topics I hadn't seen before and discovered that there was part 2 of the materials. I worked through them during the quiz."* (Liz, AP18, C).

5. DISCUSSION

This chapter provides an overview of the discussion of the results based on the research model. In addition, it proposes a model that includes the results of this thesis combined with factors found in previous literature that have influenced learners' success, understood through two different approaches. Subchapter 5.1 describes the impact of the factors influencing expectancies and value on learners' success. In subchapter 5.2, the focus is on the influence of value on learners' success. Next, an overview of the factors influenced by expectancies and value and their impact on learners' success is provided.

5.1. The impact of factors influencing expectancies and value on learners' success

The expectancy-value theory (Eccles et al., 1983) includes various factors that influence expectancies and value, and learners' background characteristics and previous experience are two factors that are discussed in this thesis. This includes learners' age, gender, participation in another online course, educational level and previous experience with programming and online courses. The influence of these two factors was examined through learners' success, based on course participants' individual intentions for the course, representing individual level expectancies. As the influence of different factors on learners' success in MOOCs is compared to course completion, the results of this thesis expand the research on this topic. The discussion in current chapter includes part of the results of RQ3.

The findings of this study show that learners' success was influenced by previous education level and experience with programming and online courses. This further emphasises that MOOC participants vary in their experiences (Jansen et al., 2020; Littlejohn et al., 2016) that affect their success. In the current thesis, education was the best predictor of success involving differently learners with a bachelor's degree or lower and learners with a master's degree or higher. This result does not confirm what was previously found when success was viewed based on the individual intentions of course participants, and no relation was found between education and success (Chaker & Bachelet, 2020). Education may impact success most, as all MOOC learners have a prior learning experience, and this can influence what the learners' intentions are regarding the course and their ability to formulate and implement the intentions. In dropout research, education has been seen to influence MOOC completion mainly in such a way that more educated learners tend to be more successful in completing the course (Gomez-Zermeno & Aleman de La Garza, 2016; Guajardo Leal & Valenzuela González, 2019; Rawat et al., 2021). However, Luik et al. (2019a) found that learners with basic education can be more successful in courses with higher difficulty levels than more educated participants. This may indicate that, regardless of the educational level, learners can be successful if they have clear intentions for the MOOC and are

ready to fulfil these.

The results of this thesis show that learners' success was also affected by previous experience with the course topic; in current thesis, computer programming. Research on MOOC completion has also found that previous experience with the course topic influences learners' performance, helping them to be more successful (Chen et al., 2020c; Reich, 2014) even in shorter and easier courses (Luik et al., 2019a). Previous experience with the topic motivates participants and gives them confidence in their skills (Alonso-Mencía et al., 2021). As previous experience with programming influenced learners with lower levels of education, topic knowledge may also affect success because it can compensate for the lack of learning skills needed to study independently in MOOCs.

Based on the results of this thesis, previous experience with online courses predicted success for learners with an education level higher than a bachelor's degree. Dropout research has also found that earlier participation in online courses affects learners' success and that those with experience are more successful (Gomez-Zermeno & Aleman de La Garza, 2016; Greene et al., 2015). However, the results of the current thesis show that most learners who participated in MOOCs for the first time could do what they intended or more. Guajardo Leal and Valenzuela González (2019) have similar findings in their dropout research. In this thesis, the learners' educational level may be the key aspect, as participants with a master's or doctorate have acquired enough learning skills to be applied in an online environment. Therefore, they may not need to contact course organisers (Khan et al., 2021; Sujatha & Kavitha, 2018) or require more feedback (Sujatha & Kavitha, 2018), which have been identified as factors correlated to dropout. Moreover, such learners may better understand what they want to gain from a MOOC and how to achieve it.

In dropout research, it has been found that in addition to learners' educational level, previous experience with course topics and online courses, their age and gender have also had an influence on their success. The findings suggest mainly that older (Chen et al., 2020c; Greene et al., 2015; Reich, 2014) and male (Crues et al., 2018; Guajardo Leal & Valenzuela González, 2019; Reich, 2014) participants are less likely to drop out from MOOCs. In previous intention-based success research, the results regarding gender were the opposite, indicating that women are more successful (Chaker & Bachelet, 2020).

As a summary, the impact of the expectancy and value influence factors on learners' success is presented in Figure 7. The figure is based on the research model of this thesis (described in sub-chapter 3.1) consisting of the studied factors and combining the results of this study and the literature review. Factors from the literature review were added to the model if a factor, in some form, influenced learners' success in the respective approach. The model shows which of the studied factors influence the success of learners based on course completion (green background) or learners' intentions (blue background). The factors affecting both approaches of learners' success are presented with green and blue colours as a

gradient. The arrows with solid lines represent the factors affecting learners' success based on the results of this thesis and the arrows with dashed lines signify the factors found from previous research.

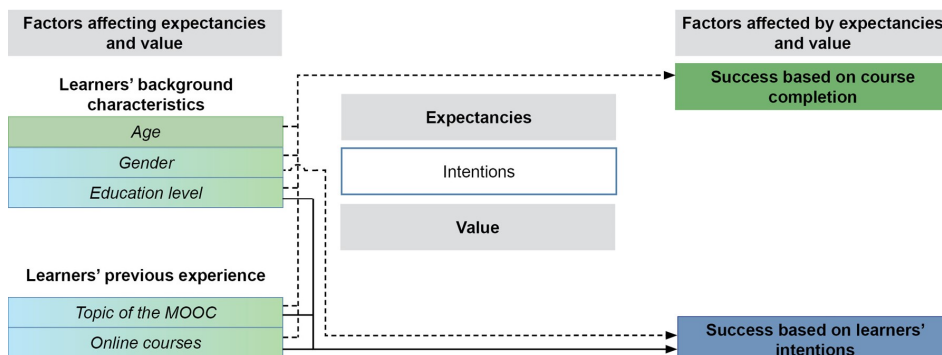


Figure 7: The impact of factors influencing expectancies and value on learners' success

This thesis' results showed that the MOOC success factors in the category of learners' background data and prior experiences were related to previous learning experience: educational level and previous experience with course topics and online courses. Gender, that has affected course participants' success in terms of course completion and intentions, and age, that has influenced course completion, were not found to have an impact on learners' success in this thesis. Success was also unaffected by learners' participation or non-participation in another online course simultaneously with learning in the current MOOC.

5.2. The impact of value on learners' success

In the expectancy-value theory (Eccles et al., 1983), cost has been interpreted as the negative aspect of value. In this thesis, cost is studied in relation to RQ4 through learners' use of time in the MOOCs and in the context of the second approach to success – course completion. A deeper study of time usage is relevant because lack of time is one of the main reasons for dropping out (Aydin & Yazici, 2020; Eriksson et al., 2017; Semenescu et al., 2020; Shapiro et al., 2017). The results in this thesis show that most course participants spent from 2 to 6 hours a week on the MOOC, which was less than they had planned. Previous research has indicated that, in addition to learners' own intentions, the time spent on the course is also shorter than the time set for the course by organisers (Shapiro et al., 2017). The results also indicate that the majority of learners would have wanted to spend more time on the course, and compared to completers, non-completers had more difficulties finding time for the course. In the learning diaries, learners pointed out multiple reasons that prevented them from investing as much time as they wanted: obligations to family and friends, health conditions, work responsibilities, vaca-

tion, learning materials and tools used in the course. Interestingly, the weather also affected the use of time in the course. Work (Eriksson et al., 2017; Onah et al., 2022; Shapiro et al., 2017), family (Eriksson et al., 2017), and social activities (Onah et al., 2022) have been noted in previous studies as well. Although learners can be successful when they spend less time on the course (Mubarak et al., 2021), current results show that compared to completers, it was more challenging for dropouts to find time for the course, and they experienced more conflicts at home or at work because of the time they spent on the course. In MOOCs, learners drop out if perceived learning costs are high (Lee & Song, 2022). Therefore, the results of this thesis may indicate that the cost of finding time and resolving conflicts was too high for dropouts, and they had to leave the course as a result. The other explanation may come from an interesting finding of this study – only completers reported that they received additional help from family members, friends or colleagues with previous programming experience, indicating that such family members, friends and colleagues may have had a better understanding of what the time spent studying was used for.

In terms of using the time, the results of this thesis showed that the main study time was at the weekend. The reasons given by learners were related to the opening of a new learning week's materials or the approach of the deadline for the current week. One of the reasons for starting early was that the topic seemed difficult. This indicates that these learners demonstrated time assessment behaviours (Claessens et al., 2007) by taking more time because they felt that the topic would otherwise be beyond their capacity. This result also confirms that the difficulty of learning materials affects the use of learners' time (Tabuenca et al., 2022) and shows that one way to keep learning on track is to start early. The learning materials and tools used also helped learners save time. The findings of this thesis show that, in addition to forum and helpdesk, even simple things, like a possibility to print the programming materials, can help save time. Tackling the course on a weekend when the deadlines of the current learning week were approaching may be due to the fact that learners mainly focus on activities with an upcoming deadline (Onah et al., 2022; Sainz et al., 2019), suggesting a rather short-term planning of time by learners (Sainz et al., 2019). Both completers and non-completers displayed planning behaviours (Claessens et al., 2007) as learning time was planned for the week. Weekly planning was adequate for the studied courses, as learning materials were opened by the week.

Both completers and dropouts monitored their time usage during the course, but only completers wrote in the learning diaries that they implemented the changes when needed. Therefore, the findings of this study show the differences in time management between completers and non-completers, as completers also demonstrated monitoring behaviours when they reduced the influence of distractions (Claessens et al., 2007). This may also be one of the reasons why dropouts could not complete the course, as managing time flexibly is more difficult than learning regularly (Li et al., 2022). On the negative side of flexible time use, learners

engaged in course activities even if they had 20-30 minutes of free time, and this approach was not sufficient for learning. Those learners had to engage in the activities again, as they could not concentrate enough in such a short period of time. Previous findings have shown that successful learners tend to study in longer sessions (de Barba et al., 2020; Lee, 2018). The findings of this thesis specify that the effective consecutive length of learning time is up to two hours, as after this period learners need help or rest.

In this study, the positive side of the value of the expectancy-value theory (Eccles et al., 1983) was studied with RQ3 through the motivation of learners to enrol on MOOCs using seven motivation factors stated in Luik et al. (2019b), including *Interest and expectancies on course*, *Personal suitability of distance learning*, *Suitability for family and work*, *Importance and perceived ability*, *Usefulness related to certification*, *Social influence*, and *Usefulness related to own children*. The only motivation factor that affected learners' success when success was based on learners' intentions for the course was *Usefulness related to certification*. The influence of certification appeared only in the case of highly educated learners with previous online course experience. Earning a certificate may not be the leading reason learners enrol on MOOCs (Reparaz et al., 2020), but dropout research has found that interest in certificates can motivate learners to complete the course (Chen et al., 2020c; Luik et al., 2018). The results of this thesis show that most learners who rated the usefulness of certification highly were able to fulfil their intentions. As these learners have participated in online courses before and value certificates, they may collect the certificates because they believe that MOOC certificates give them an advantage in the job market (Elsayed Mohamed & Ali, 2018).

In dropout research, in addition to usefulness of certification, interest in the course, participants' ability to learn in online courses and combine learning with work and family life, and the social influence of family and friends have been identified as factors influencing dropout from MOOCs. Compared to non-completers, completers are more motivated to enrol on MOOCs because they are interested in gaining knowledge about the topic (Reparaz et al., 2020) and they find that distance learning suits them (Luik et al., 2018). Dropouts have pointed out several reasons why they were not able to complete MOOCs, including their other studies (Aydin & Yazici, 2020), work (Aydin & Yazici, 2020; Semenescu et al., 2020) and family life (Aydin & Yazici, 2020; Eriksson et al., 2017). The perceived success of a learner in the eyes of friends and family is more motivating for completers (Luik et al., 2018).

Figure 8 is a continuation of Figure 7. In addition to the factors influencing expectancies and value, it also presents the effect of value on learners' success. The arrows with double lines show the factors that have affected learners' success based on the results of this thesis and previous research.

The impact of value on learners' success can be summarised as follows: The results of this thesis about the use of time, which has been previously identified

as one of the main reasons learners drop out of MOOCs, revealed several differences between completers and non-completers. Dropouts had more difficulty finding time for the course, and they encountered more conflicts at home and at work in relation to studying in the MOOC. Only completers were helped with the course activities by their friends, colleagues or family members and implemented changes in their time usage when needed.

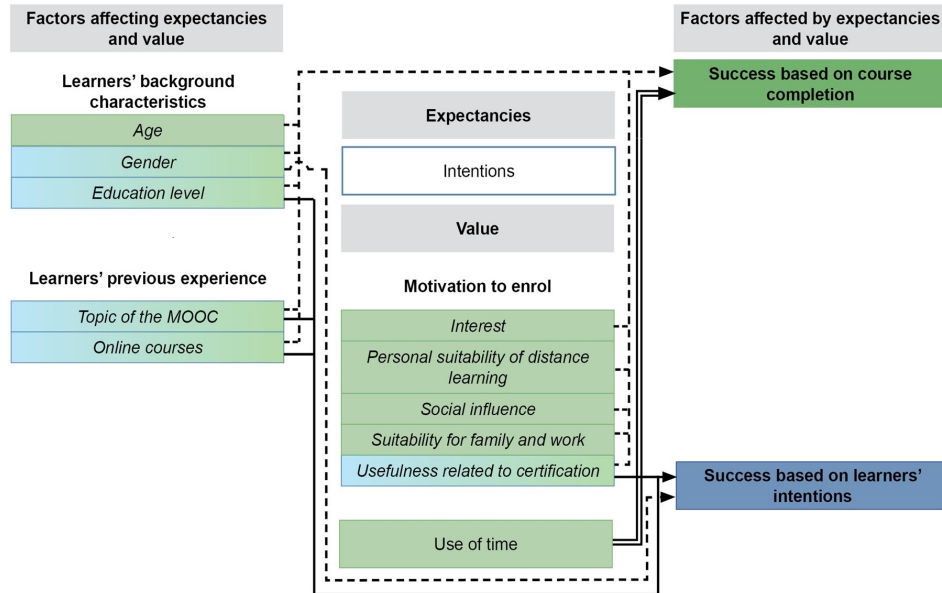


Figure 8: The impact of factors influencing expectancies and value and value on learners' success

From the positive side of the value perspective that represented motivation to enrol on a MOOC in this study, the only motivational factor affecting learners' success based on their intentions was related to the usefulness of the MOOC certificate. In previous research, course completion has been seen to be influenced by motivational factors related to learners' interest in the course, their suitability to learn in online courses and balance learning in a MOOC with work and family life, social influences, and earning a certificate.

5.3. The impact of factors influenced by expectancies and value on learners' success

Based on the expectancy-value theory, expectancies and value impact learners' persistence, performance (Eccles & Wigfield, 2002) and engagement (Jiang & Zhang, 2023). In this thesis, persistence was defined through course completion. The study was aimed at finding what are the periods with the highest dropout rates (RQ1), how learners performed in mandatory course activities before drop-

ping out (RQ2), and how the choices regarding the performance of the MOOC activities affected dropping out (RQ5). The other definition of success, based on learners' intentions, was used to study the effect of engagement (RQ3), which was the estimation of how many of the eleven course activities learners planned to perform.

The results showed that in all studied courses, the highest dropout rate was at the beginning of the course, more precisely, in the first two weeks. This was followed by a dropout stabilisation in the second half of the shorter and easier courses and in the middle of the longer and more difficult courses. The courses studied in this thesis differed in their level of difficulty. Therefore, it can be concluded that a course's difficulty level does not affect the timing of the periods with the highest dropout. In IP2, one more peak in the dropout rates occurred towards the end of the course, before learners started with the project. In general, these results align with previous research that has similarly shown that dropout occurs primarily early in the course (de Freitas et al., 2015; Greene et al., 2015; Ihantola et al., 2020) before stabilisation (de Freitas et al., 2015). However, when comparing the results of studies, it must be remembered that dropout does not have a uniform definition and, therefore, it can be approached differently in different studies, which may affect the number of reported dropouts per week.

To complete a course, learners had to complete the mandatory activities successfully. Completing mandatory activities has been found as a predictor of course completion in previous research (Isidro et al., 2018). To succeed, learners were provided with different activities designed to help them learn the course topics. The results of this thesis suggest that learners followed the order set by course organisers regarding the sequence of activities. Therefore, it indicates that the provided sequence of activities matches the course participants' learning habits (Onah et al., 2021). As a slight difference from the given sequence, all the reading materials were engaged with as a first step. According to previous research, reading materials are used more often by completers (Kim & Park, 2022). In the current thesis, after finishing with the reading materials, programming exercises were solved, although only the programming materials provided the knowledge for solving programming exercises. While tackling the reading materials, learners used other activities that were offered in these materials, like videos and self-assessment questions. Previous research has not found any differences between completers and non-completers regarding viewing videos (Kim & Park, 2022). However, rewinding videos at the beginning of the course has been noted as a predictor of dropout (Isidro et al., 2018). The results of this thesis highlight the importance of self-testing, as almost all learners used self-assessment questions. This may indicate that course participants needed the self-assessment questions to test their knowledge and found these useful, as learners in MOOCs choose activities based on their own needs (Zheng et al., 2015) and usefulness of the activities (Ding & Shen, 2022). As some learners used the self-assessment questions as their first activity, it shows that these questions were not used only to test the

knowledge gained during learning, but also for testing if they already knew the topic. Self-assessment questions were also the only activity in which completers and dropouts differed in the sequence of activities. Dropouts used self-assessment questions later in the sequence. This finding does not support the result of Pigeau et al. (2019), where no difference was found for completers and dropouts regarding the sequence of their activities. Current findings may indicate that completers used self-assessment questions when they read the learning materials, whereas dropouts did it when they had issues with mandatory activities. Therefore, they had to revisit learning materials and test their knowledge with self-assessment questions.

When learners' performance before dropping out was studied, the results showed that in the first two weeks of the shorter and easier courses, where the dropout rate was highest, most learners who dropped out managed to complete all the mandatory activities until dropping out. According to the expectancy-value theory, this kind of learner behaviour may show the low value of course activities, as learners are unwilling to invest more effort in the MOOC even if they are successful in the course (Brophy, 2013). However, although learners mainly used the activities that helped them understand the topic and solve the mandatory exercises, they also engaged in activities unrelated to course completion or mandatory activities. First, in reading materials, there were links to external resources. When learners' success was viewed based on their intentions, success was found to be influenced by the amount of external materials course participants intended to visit. Engaging with these materials shows that learners are willing to invest additional resources into learning in MOOCs and consequently do more in the course than they initially intended. However, participants in MOOCs often do not have additional resources, such as time, as lack of time is one of the main reasons why they leave the course before the end (Aydin & Yazici, 2020; Eriksson et al., 2017; Semenescu et al., 2020). Therefore, the activities learners intend to do may not be done in reality, as they invest their resources in additional activities. Second, an interesting finding is that only a few learners did not read literary stories. This result differs from previous findings where learners have been seen to prefer activities that benefit them (Beymer et al., 2022), but literary stories did not affect course completion in this case. However, it may suggest that these stories were interesting, as learners also use activities that interest them (Beymer et al., 2022).

Learners' performance during the first two weeks of the shorter and easier courses indicates that learners did not drop out because of the challenging content. The fact that they had completed all the required course activities by the time of dropout may indicate that learners have been influenced by factors external to the course that also affected their use of time in the course, such as high workload (Eriksson et al., 2017; Onah et al., 2022; Shapiro et al., 2017), other studies, family issues (Eriksson et al., 2017) and even the weather. The properties of a MOOC can also affect the performance of learners. "About Programming" is a short introductory course. Therefore, these learners may not value the knowledge

gained from this MOOC or do not find the content challenging enough. Previous research has shown that participants in MOOCs want challenging activities (Hew, 2018), and they leave at the beginning of the MOOC if the course turns out to be not suitable for them (de Freitas et al., 2015; Ihantola et al., 2020; Lu et al., 2017; Zhang et al., 2021).

Based on current results, to challenge themselves, learners skipped the activities that would have made solving the mandatory activities easier. However, previously it has been found that learners who take part in more activities are more likely to complete the course (Lee, 2018). On the one hand, in the case of problems in solving mandatory activities, course participants used other activities to get help or returned to the learning materials. Previous findings have also shown that revisiting learning materials takes place after failing in graded activities (Janakiraman et al., 2018). In addition, completers revisit more activities compared to dropouts (Conijn et al., 2018). On the other hand, when learners solved the mandatory activities successfully, they skipped supportive activities like the forum or troubleshooters. This may explain why the forum and troubleshooters were the least used activities in the studied courses. Previous findings also indicate that forums are rarely used (Conijn et al., 2018; Janakiraman et al., 2018). The way learners use the forum has shown that learners who participate (Semenova, 2022) in the forum, including by commenting (Tang et al., 2020) and posting (Cruet et al., 2018; Tang et al., 2020), are more likely to stay in the course. Current results match the findings of Cruet et al. (2018) that helping others is one of the reasons why learners use the forum.

Another type of learners' behaviour occurred in the third week of the shorter and easier courses and in the first half of the longer and more difficult courses, where most dropouts completed all the required activities before the dropout week but not during the dropout week. Therefore, it can be concluded that learners' performance affects their success in the second half of shorter and easier, and in the first half of longer and more difficult courses. On one hand, based on the expectancy-value theory, the results indicate that learners drop out as they invest reasonable effort in completing the activities but do not achieve success (Brophy, 2013). This may indicate a relation with the complexity of the course content as programming has been considered a complex skill to learn (Babori, 2022; Gomes & Mendes, 2014), especially for beginners (Babori, 2022). On the other hand, participants may have not been able to invest enough effort in learning because of conflicts at home or at work over the time spent on the course. In IP2 that required previous programming experience, learners may have overestimated their programming knowledge and, therefore, had problems completing the activities. In addition, IP2 had no helpdesk and learners may not have received the help they needed from other supporting activities. The results from the learning diaries also show that if the previous way of learning did not bring the expected results, learners changed the way they used the course activities. Although prior results show that many learners in MOOCs are not able to monitor their learning process

(Jansen et al., 2022), this result may suggest that the participants who understand that they need to make changes in their learning and implement the changes are the ones who can alter their sequence of activities to fulfil their personal needs (Littlejohn et al., 2016). The results of this study also indicate that these learners lacked time management skills as completers' good time management skills help them make changes in the learning that also affect the sequence of activities.

Interestingly, of the learners who dropped out in the fourth week of the shorter and easier courses, more than one-third submitted mandatory activities in the last week, having not completed any previous weeks. First, this may indicate, as has been found in previous studies, that learners may have individual intentions for MOOCs (Henderikx et al., 2017; Shapiro et al., 2017), and not all learners intend to complete the course and get a certificate (Shapiro et al., 2017). Therefore, they engage only in the activities that help them fulfil their intentions. Second, course participants also do not perform activities when they already have the knowledge that these activities provide (Jansen et al., 2022). This may suggest that learners with previous programming experience can skip some activities when they are familiar with the topic. When no new knowledge is gained, even mandatory activities can be skipped to save time spent on the course. The third explanation might be that the activities are not done because participants do not have relevant skills for some activities (Albelbisi, 2019). In the current course, not all learners performed mandatory activities. Therefore, this may indicate that these were too difficult for some learners. This result may also show that the cost of engaging in some activities may be too high, as activities are avoided when they are costly (Beymer et al., 2022).

Over half of the learners who dropped out towards the end of IP2, before the project, had completed all previous weeks but did not submit the project. This result agrees with the earlier findings (Lu et al., 2017; Sabanwar et al., 2022). Leaving before the project may indicate that the course did not prepare these learners for completing the project (Kinnunen & Malmi, 2006). However, all submitted projects were completed, including projects of the learners who did not complete some of the previous learning weeks. Therefore, dropped-out learners might have learned the relevant concepts (Sabanwar et al., 2022) without completing the project as the project should have been conducted based on what was already learned in the course and did not add any new topics.

In addition to the factors reflected in Figure 8, Figure 9 also includes factors that are influenced by expectancies and value. Therefore, Figure 9 represents a model as a summary of the discussion including all the studied factors and their effect on learners' success.

In summary, regarding the factors affected by expectancies and value, the main dropout time was at the beginning of the MOOCs and towards the end of the course if the MOOC included a project. Previous dropout research has shown that completing mandatory activities predicts course completion. In the current study, performance affected dropping out in the second half of the shorter and

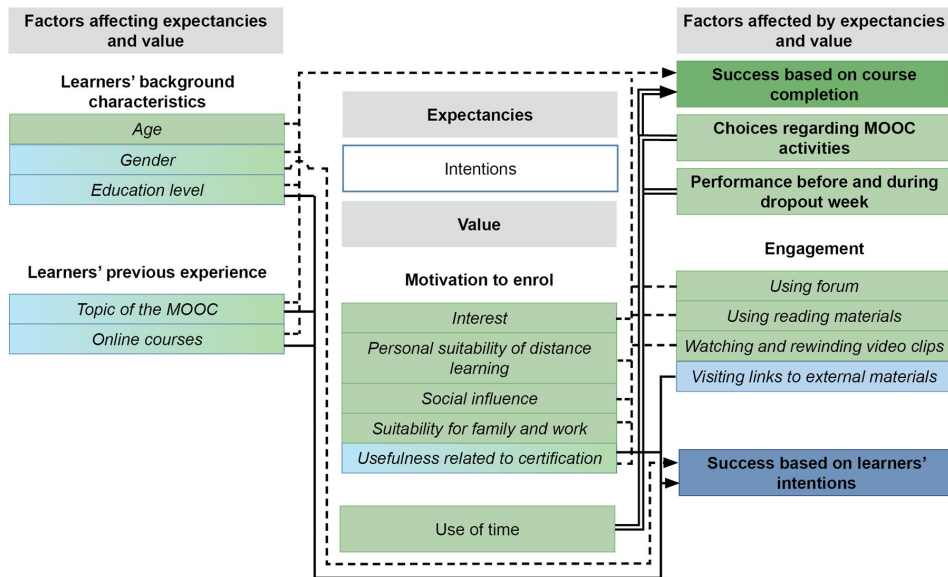


Figure 9: Model of factors affecting learners' success

easier courses and in the first half of the longer and more difficult courses when participants completed all the relevant activities until the dropout week but did not complete all the activities on the week they dropped out. Course activities were mainly performed in the sequence set by course organisers, and learners used mandatory and non-mandatory activities. In previous dropout research, completers have been seen to participate in more activities and to revisit more activities compared to non-completers. The only difference in the sequence of activities between completers and dropouts was in the case of self-assessment questions. The volume of external materials learners planned to engage with was the only course activity influencing learners' success based on their intentions. Based on the previous dropout research, using reading materials, watching and rewinding video clips and participating in a forum can affect course completion.

6. CONCLUSION AND IMPLICATIONS

This chapter provides the conclusions with the theoretical, methodological, and practical implications, limitations of the studies and suggestions for future research. This thesis used quantitative dominant mixed methods research based on the expectancy-value theory to determine which and how different factors affect learners' success in CP MOOCs. A model for two different approaches to learners' success and the factors affecting it was presented based on the results of this thesis and previous research. Success based on learners' intentions for the MOOC was influenced by learners' education level, previous experience with course topic and online courses, usefulness of the course certification and visiting the links to external materials. In addition, previous results have shown learner's gender also to be an influence factor. Based on this and previous research, course completion was affected by learners' use of time, choices regarding the MOOC activities and performance before dropping out. Previous results have shown that, from the factors characterising motivation to enrol, course completion was impacted by interest, personal suitability of distance learning, social influences, and suitability for family and work. In addition, engagement has an effect through using the forum and reading materials and rewinding video clips. The results of this thesis can be useful for the creators of MOOCs, as by knowing the factors that affect learners' success, it is possible to support learners in achieving success and making the organisation of the course more cost-effective.

6.1. Implications

First, the theoretical implications are presented.

- The results of this thesis extend the theoretical background related to an intention-based understanding of learners' success by adding factors about learners' background characteristics and previous experience, motivation to enrol and engagement that have influenced success in MOOCs. More specifically, success was affected by learners' education level, previous experience with course topic and online courses, usefulness of the course certification and visiting the links to external materials. The influencing factors found in this study and previously found factors are presented in Figure 9.
- A model (Figure 9) was presented to reflect the factors that influence learners' success based on their intention for the MOOC and completion of the MOOC. This model can be a theoretical basis for further research on learners' success and the factors affecting success.

Second, methodological implications are given to consider in future studies related to learners' success.

- In qualitative research related to learners' success in MOOCs, interviews

have been used as the main data collection instrument (e.g. Eriksson et al., 2017; Shapiro et al., 2017; Zheng et al., 2015). Based on this research, it can be concluded that using learning diaries to collect data is also a suitable option. Interviews are primarily conducted at the end of the course (e.g. Eriksson et al., 2017; Shapiro et al., 2017); however, learning diaries allow learners to continuously evaluate and reflect on their learning process (Debbag & Fidan, 2020) throughout the course. In addition, the content of the learning diaries showed that it did not depend on the questions given to learners. They wrote about the topics and emotions that were important to them at the time of writing.

- The influence of different factors on learners' success has been studied using various data analysis methods, for example, survival (Chen et al., 2020c; Greene et al., 2015), logistic regression (Reich, 2014; Semenova, 2022) and correlation analysis (Romero-Rodríguez et al., 2020). Although the decision tree algorithm is a powerful data mining technique that enables understanding relationships between independent and dependent values easier (Song & Lu, 2015), it has not been widely used in the research on learners' success. This study showed that the decision tree algorithm is also one of the appropriate data analysis methods to use in case of the influence of different factors on learners' success.

Third, practical implications are presented that could be considered when creating MOOCs to contribute to the learners' success.

- Compared to completers, non-completers used self-assessment questions later in the sequence of the MOOC activities. Therefore, first, course organisers should favour self-testing the knowledge presented in the reading materials during or even before reading if learners want to determine how familiar they are with the topic. This enables learners to reflect and get direct feedback on the topic before applying this knowledge to mandatory activities. Second, learners who have problems with mandatory activities should be directed to self-assessment questions. It helps learners review what they have learned and highlights areas that need revision.
- The different intentions of learners for MOOCs allow course organisers to reconsider the resources spent on the course. Some participants in a course may not have the intention to complete the course, which means that such learners do not need the support that is relevant for course completion. Therefore, support resources can be reduced or relocated. This applies especially to the human resources of the organisers, such as the helpdesk in some of the courses discussed in this thesis. As troubleshooters and the forum were the least used activities, learners should be directed there instead of using the helpdesk because maintaining troubleshooters and a forum is more cost-effective. However, support mechanisms should be versatile to

meet the needs of learners with different intentions.

- Learners' success based on their intentions was affected by their previous learning experience. Therefore, a MOOC should support learners with different educational experiences. Providing course activities with various difficulty levels may be helpful. On the one hand, example exercises could help learners with their issues with mandatory activities. On the other hand, more difficult example exercises could be provided to challenge learners. For instance, these exercises could allow learners to see the application of the learned concept in a more complex situation or offer several alternative solutions to one exercise. Additional materials provide support to learners who need more explanations to understand the topic or create opportunities for a deeper understanding of the topic. In addition, course materials may include instructions on how to learn in online courses.
- Learners drop out of MOOCs towards the end of the course when the course includes a project. The project allows learners to use what they have learned during the course as a whole, applying knowledge and skills in practice, thereby creating something larger in terms of content than what the exercises by topic have required. To encourage learners to participate in the project, sample projects and topics can be presented, giving learners a better overview of the project's scope and providing ideas. Learners themselves must complete the project according to the requirements and knowledge gained from the MOOC. For some learners, it could be useful to do a project in pairs or groups, so that there is someone to exchange ideas with and help each other. However, learners who do not intend to finish the project but have completed everything necessary before the project have acquired the knowledge provided in the course. Therefore, these learners can be offered an opportunity to receive a separate course certificate, which reflects the smaller volume of study and respective course credits.

6.2. Limitations and suggestions for future research

This thesis has some limitations that need to be considered when generalising the results.

- In this thesis, the focus was only on computer programming MOOCs. Given the complexity of programming education for beginners, the factors influencing learners' success in other topics in MOOCs may be different. In addition, the studied courses were homogeneous, which may affect the generalisability of the results.
- Pre- and post-questionnaires, which were self-assessment instruments, were used to collect data about learners' use of time and course activities, intentions, engagement, and motivation. Questionnaires are often used for collecting data about learners' behaviour and attitudes. However, learners may

over- or underestimate the time used in the course, as well as their intentions, motivation, or engagement. They could also generalise their use of activities as they may differ at the beginning and end of the course. Therefore, the results may not reflect the learners' actual behaviour. Collecting data continuously during the course can give more accurate self-assessment results.

- Only learners who filled out the pre- and post-questionnaires or wrote the learning diaries were included in this study of learners' intentions, use of time and course activities, engagement, and motivation. Learners who participated in the data collection process may also represent more motivated learners. Therefore, there might be differences between these learners and the learners who were not included in the study and some bias may exist in the conclusions.
- Writing the learning diaries and answering the pre- and post-questionnaires was an optional activity. Therefore, fewer non-completers than completers wrote the learning diaries and answered the post-questionnaires. This did not allow for a more comprehensive comparison of the completers and non-completers use of time and course activities.

Suggestions for further research are presented as follows:

- Although this study widens the research on success based on learner's intentions, only a few factors were included and the examination of their influence on learners' success was limited to one kind of courses on a particular topic. Future research can add different course factors and examine the effects of these factors. Various research methodologies could be used; for example, qualitative research could be conducted in addition to quantitative research. The changes in learners' intentions during a course and the possibilities for course organisers to react to them can provide a useful topic for research.
- There are also multiple factors affecting learners' success that need further research. The results of this study showed that previous learning experience influenced success based on the learners' intentions in terms of background factors and previous experience. Therefore, further research of these factors could start by studying which intentions learners with different educational levels and previous experience have towards MOOCs and how previous educational level and experience affect learners' success. The need for further research is also emphasised by previous dropout studies that have not found consistent results regarding these factors. Furthermore, although the results of this thesis did not show that the gender of the learners affected their success, the literature has shown conflicting results between different approaches to success and gender's effect on these. Therefore, further investigation is needed to determine which intentions learners of different

genders have and how they can fulfil these intentions.

- Activities offered in a course affect learners' success: self-testing from the perspective of course completion and visiting additional materials from the intention perspective. More in-depth knowledge about the use of these activities would advance the understanding of how learners use these activities, the impact they have on success, and how the learners for whom the activities would be helpful could be guided to them. In addition, further knowledge helps course organisers develop these activities to provide a better fit for learners' expectations.
- A certificate and the associated benefits can motivate learners to enrol in MOOCs. During the course, however, it can be seen from learners' behaviour that getting a certificate is not always the main focus. Therefore, why a certificate is useful for learners and how they can use it after the course should be investigated. This knowledge also helps to develop MOOCs further so that the course, through certification, meets the needs of learners and outside stakeholders (for example, in the labour market).
- In this thesis, the results showed that non-completers' performance differed before dropping out. Therefore, further research could focus on non-completers, as there is a lack of information on why learners perform differently and drop out of MOOCs. Possible research topics could address dropouts' intentions for MOOCs and the use of time.
- Compared to regular completion rates in MOOCs, the courses studied in this thesis had high completion rates. In the future, comparing these courses with other computer programming MOOCs would be useful in finding the reasons that influenced course completion.
- In recent times, the development of technology, especially artificial intelligence (AI), has brought about changes in the field of education. Therefore, future research could also address how course organisers and learners use AI in MOOCs and how this affects learners' success.

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SISUKOKKUVÕTE

Mitu lähenemisviisi õppijate edule ja seda mõjutavad tegurid programmeerimise MOOCidel

Tänapäeva ühiskonnas mõjutab tehnoloogia kõiki eluvaldkondi ning tehnoloogia loomine ja kasutuselevõtt vajab inimestelt uusi teadmisi ja oskuseid. Üheks oluliseks oskuseks on programmeerimine (Bey et al., 2018) ning programmeerimist oskavaid inimesi on järjest enam vaja (OECD, 2022). Uute teadmiste ja oskuste omandamiseks on elukestev õpe saanud osaks inimeste igapäevaelust (Kaplan, 2016). Õppimine vaba juurdepääsuga e-kursustel (ingl *massive open online course*, MOOC) on üks võimalus, et osaleda elukestvas õppes. MOOCid on veebipõhised kursused, kus kõik soovijad olenemata enda taustast, kogemustest ja asukohast saavad internetiühenduse olemasolul tasuta osaleda. MOOCid pakuvad paljudele ligipääsu kvaliteetsele haridusele (de Freitas et al., 2015). On aga tõstatatud küsimus, kui efektiivsed MOOCid tegelikult õppijate edu arvestades on (Romero-Rodríguez et al., 2020; Sabanwar et al., 2022), kuna väikest kursuse lõpetajate arvu on peetud üheks MOOCide probleemiks (Goopio & Cheung, 2020; Khan et al., 2021; Sabanwar et al., 2022; Vitiello et al., 2018).

MOOCide spetsiifilised omadused ja õppijate mitmekesine taust on seotud ootuste-väärtuste teooriaga (ingl *expectancy-value theory*) (Lee & Song, 2022). See teooria (Eccles et al., 1983) on oluline õppijate õppeedukuse mõistmiseks ja võimaldab uurida osalejate valikuid kursusel osalemise ajal ja nende soovi jätkata MOOCidel õppimist (Lee & Song, 2022). Seetõttu on doktoritöö aluseks ootuste-väärtuste teooria. See teooria keskendub kahele aspektile. Esiteks näitab ootus inimeste uskumusi selle kohta, kui hästi nad mingi tegevusega hakkama saavad (Eccles & Wigfield, 2020). Teiseks näitab tegevusele omistatav väärtus, mil määral vastab tegevus vajadustele ja isiklikele väärtustele ning aitab täita püstitatud eesmärgi (Eccles et al., 1983).

MOOCidel on õppijate edu aluseks enamasti peetud kursuse lõpetamist. Ootuste-väärtuste teooria vaatest käsitletakse kursuse lõpetamist kui kursusel püsimist (ingl *persistence*) (Lee & Song, 2022). MOOCil püsimist mõjutavad õppijate ootused ja väärtused (Eccles & Wigfield, 2002). On uurijaid, kes on leidnud, et edu ei peaks vaatama mitte läbi kursuse lõpetamise, vaid läbi õppijate individuaalsete kavatsuste (Henderikx et al., 2017; Reich, 2014). See tähendab, et edukad on need õppijad, kes teevad kursusel nii palju kui nad plaanisid või rohkem. Mitte- edukateks loetakse need, kes teevad planeeritust vähem (Henderikx et al., 2017). Ootuste-väärtuste teoorias ootused väljendavad individuaalseid uskumusi (Eccles & Wigfield, 2002) selle kohta, kui hästi eelseisva tegevusega hakkama saadakse (Eccles & Wigfield, 2020). Doktoritöös käsitletakse ootuseid kui kavatsusi kursuse suhtes. Edu vaadatakse lähtudes kahest aspektist: kursuse lõpetamisest ja õppijate kavatsustest.

Õppijate edu mõistmiseks tuleb uurida, millised faktorid seda mõjutavad. Doktoritöösse valiti faktorid, mis lähtuvad ootuste-väärtuste teooriast. Selle teooria järgi on väärtused jagatud neljaks alamkomponendiks: huvi-naudingu väärtus (ingl *intrinsic value*), kasulikkuse väärtus (ingl *utility value*), saavutusväärtus (ingl *attainment value*) ja kulu (ingl *cost*). Kolm esimest väärtuste alamkategoriat aitavad aru saada MOOCide väärtuse positiivsest poolest (Eccles et al., 1983). Nende kaudu on võimalik kirjeldada motiive, miks õppijad MOOCidele registreeruvad (Lee & Song, 2022). Doktoritöös keskendutaksegi kursusele registreerumise motivatsioonile ning seda uuritakse seoses õppijate eduga, mis lähtub nende kavatsustest. See lähenemine valiti, kuna enamasti on MOOCide puhul õppijate motivatsiooni uuritud seoses kursuse lõpetamisega (Chen et al., 2020a, Luik & Lepp, 2021, Reparaz et al., 2020). Registreerumise motivatsiooni on oluline uurida, kuna see võimaldab varakult näha võimalikke takistusi ja eeliseid, mis õppijatel MOOCidega seoses võivad olla (Maya-Jariego et al., 2020) ning see on ka üks faktor, mis mõjutab kursuse lõpetamist (Luik et al., 2018).

MOOCide kontekstis on kulud seotud eesmärkide saavutamisel tekkivate takistuste ületamisega ja investeeritud ajaga (Chen et al., 2020b). Halb ajajuhtimine on olnud üks peamisi MOOCidelt väljalangemise põhjuseid (Nawrot & Doucet, 2014). Seetõttu loetakse doktoritöös õppijate aja kasutamist kursusel osalemise kuluks ning seda uuritakse seoses kursuse lõpetamisega. Oluline on see, kuidas õppijad enda aega kasutada oskavad (Sainz et al., 2019). Doktoritöös keskendutaksegi õppijate aja kasutamisele ning faktoritele, mis seda mõjutavad.

Lisaks ootustele ja väärtustele on ootuste-väärtuste teooria (Eccles et al., 1983) autorid kajastanud ka tegureid, mis otseselt või kaudselt mõjutavad ootuseid ja väärtuseid ning tegureid, mis on mõjutatud ootustest ja väärtustest. Ootuste ja väärtuste mõjutajateks on õppijate taustaandmed ja varasemad kogemused ning need on doktoritöös olulised, sest MOOCidel osalejatel on väga erinevad kogemused ja taust (Li, 2019). Taustaandmete mõju õppijate edule uuritakse lähtudes õppijate kavatsustest kursuse suhtes. Ootused ja väärtused mõjutavad õppijate sooritust (ingl *performance*) ning seda, kuidas õppijad tegevusi valivad (Eccles & Wigfield, 2002). Tegevuste valik avaldab mõju ka tegevuste sooritamise järjestusele (Chen et al., 2020b). Õppijad ei pea järgima MOOCidel kursuse korraldajate poolt seatud tegevuste järjekorda (Wong et al., 2019). Veebipõhises õpikeskkonnas eeldatakse, et õppijad kontrollivad autonoomselt enda õppimist (Onah et al., 2021), kuid on neid, kes seda tõhusalt teha ei oska (Albelbisi, 2019). Seetõttu on oluline teada, miks õppijad teevad enda valikuid ja kuidas need mõjutavad edu MOOCil. Õpisooritust ja tegevuste valikut uuriti doktoritöös seoses kursuse lõpetamisega.

Kursuse tegevuste kasutamisel on oluline roll ka õppijate kaasatuse puhul (ingl *engagement*). Kaasatust MOOCidel uuritakse sageli lähtudes käitumuslikust kaasatusest (ingl *behavioural engagement*) keskendudes kursuse tegevuste sooritamisele (Anutariya & Thongsuntia, 2019; Semenova, 2022). Kaasatuse uurimine selles doktoritöös on oluline, kuna kaasatust peetakse MOOCi keskkonnas õppi-

jate edu keskseks määrajaks (Anutariya & Thongsuntia, 2019). Ootuste-väärtuste teooria kontekstis on õppijate kaasatus üks faktoritest, mis on mõjutatud nende ootustest ja väärtustest (Jiang & Zhang, 2023). Kaasatust uuritakse doktoritöös lähtudes õppijate kavatsusest kursuse suhtes.

Doktoritöö raames viidi läbi uurimus kasutades kombineeritud uurimismeetodit. Eesmärk oli välja selgitada, millised tegurid ja kuidas need mõjutavad õppijate edu programmeerimise MOOCidel. Kursustena vaadati kolme Tartu Ülikooli arvutiteaduse instituudi informaatika didaktika töörühma poolt loodud ja läbi viidud programmeerimise MOOCi: „Programmeerimisest maalähedaselt“ (Publikatsioon I-IV), „Programmeerimise alused“ ja „Programmeerimise alused 2“ (Publikatsioon II). Kvantitatiivsed andmed koguti eel- (Publikatsioon II-IV) ja järelankeediga (Publikatsioon III-IV), õpikeskkonnast Moodle (Publikatsioon I) ning Tartu Ülikooli õppeinfosüsteemist (Publikatsioon II). Kvalitatiivsete andmete kogumiseks kasutati õpipäevikut (Publikatsioon III-IV).

Doktoritöös uuriti faktoritest, mis mõjutavad õppijate ootuseid ja väärtuseid, õppijate taustaandmeid (sugu, vanus, haridus, osalemine teisel veebipõhisel kursusel) ja varasemat kogemust (programmeerimise ja veebipõhise õppega). Tulemused näitasid, et õppijate haridustase ning varasem kogemus programmeerimise ja veebipõhise õppega mõjutasid õppijate edu lähtudes nende kavatsusest kursuse suhtes (Publikatsioon II).

Väärtuste negatiivseid aspekte kirjeldava aja kasutamise osas näitasid tulemused (Publikatsioon III), et õppijad tegelesid kursusega kõige sagedamini nädalavahtetusel. MOOCile kulutati vähem aega, kui esialgselt planeeriti. Lühikesed, kuni 30-minutilised, õppimisperioodid ei olnud keskendumiseks piisavad. Optimaalne aeg ülesannete lahendamiseks oli kuni kaks tundi. Pärast seda vajasid õppijad abi või pausi. Õppijate aja kasutamist kursusel mõjutavad nende isiklik elu, tööl käimine, terviseprobleemid, puhkus ja ilm. Aja kasutamises esines mitmeid erinevusi kursuse lõpetajate ja väljalangejate vahel. Mittelõpetajatel oli raskuseid kursuse jaoks aja leidmisega ning neil tekkis rohkem konflikte kodus ja tööl seoses MOOCil õppimisega. Erinevalt mittelõpetajatest said lõpetajad kursuse tegevuste lõpetamiseks abi sõpradelt, kolleegidelt ja pereliikmetelt ning tegid vajadusel enda ajakasutuses muudatusi. Väärtuste positiivset külge esindas selles uurimuses MOOCile registreerumise motivatsioon. MOOCilt saadava tunnistuse kasulikkus (ingl *Usefulness related to certification*) oli ainus motivatsioonitegur, mis mõjutas õppijate edu nende kavatsustest lähtudes. Teised uuritud faktorid, milleks olid huvi ja ootused kursuse suhtes (ingl *Interest and expectancies on course*), sobivus veebipõhiseks õppeks (ingl *Personal suitability of distance learning*), sotsiaalne mõju (ingl *Social influence*), tähtsus ja tajutud võimekus (ingl *Importance and perceived ability*), sobivus töö ja perega (ingl *Suitability for family and work*), enda lastega seotud kasulikkus (ingl *Usefulness related to own children*), mõju ei omanud (Publikatsioon II).

Faktoritest, mis on mõjutatud ootustest ja väärtustest, mõjutasid edu MOOCil õppijate sooritus (Publikatsioon I), tegevuste valik (Publikatsioon IV) ja kaasatu-

sega seoses üheteistkümnest uuritud kursuse tegevusest ainult välistele materjalidele viitavate linkide külastamine (ingl *links to external materials*) (Publikatsioon II). Kaasatust uuriti lähtudes õppijate kavatsustest kursuse suhtes, teisi faktoreid seoses kursuse lõpetamisega. Sooritus mõjutas väljalangemist lühemate ja kergemate kursuste teises pooles ning pikemate ja raskemate kursuste esimeses pooles. Osalejad tegid siis ära kõik kursuse kohustuslikud tegevused kuni väljalangemise nädalani, kuid ei lõpetanud kõiki tegevusi sellel nädalal, kui nad kursuse pooleli jätsid. Kõige rohkem väljalangejaid oli kõigi uuritud kursuste korral kursuse alguses. Kui kursuse lõpus oli projekt, siis tõusis mittelõpetajate arv ka kursuse lõpu poole (Publikatsioon I). Uurimuse tulemused näitasid ka, et peamiselt järgisid õppijad kursusel ette antud tegevuste järjekorda. Kõige rohkem tehti neid tegevusi, mis aitasid kursuse materjalist aru saada ja kursuse lõpetamiseks vajalikke teste ja ülesandeid lahendada. Siiski tegeleti ka tegevustega, mis otseselt kursuse lõpetamisega seotud ei olnud, näiteks maalähedaste lugude lugemisega (ingl *literary stories*). Tegevuste järjekorda mõjutasid testide ja ülesannete lahendamiseks ettevalmistamine ning see, kui edukalt õppijad testide ja ülesannete lahendamisega hakkama said. Näiteks, kui lahendamine ei õnnestunud, pöörduti tagasi õppematerjalide juurde või kasutati lisaks toetavaid kursuse vahendeid. Ainus erinevus lõpetajate ja mittelõpetajate tegevuste järjestuses oli enesehindamise küsimuste (ingl *self-assessment questions*) puhul, kus lõpetajad vastasid nendele küsimustele tegevuste järjekorras varem.

Doktoritöö tulemuste ja varasemate uurimuste tulemuste põhjal koostati mudel, mis kajastab õppijate edu erinevaid lähenemisi ning neid mõjutavaid faktoreid. Mudel koosneb kolmest osast ning toetub ootuste-väärtuste teooriale (Eccles et al., 1983). Mudeli esimene osa näitab faktoreid, mis mõjutavad ootuseid ja väärtuseid – õppijate taustaandmed ja varasem kogemus. Selle uurimuse tulemuste põhjal mõjutavad õppijate edu lähtudes nende kavatsustest õppijate haridustase ja eelnev kogemus kursuse teema ning veebipõhise õppega. Varasemate uurimuste põhjal on mõjutajaks ka õppijate sugu. Kui õppijate edu on vaadatud läbi kursuse lõpetamise, on varasemad tulemused näidanud, et õppijate edu mõjutajateks on õppijate vanus, sugu, haridus ning eelnev kogemus kursuse teema ja veebipõhise õppega.

Mudeli teine osa näitab, missugused väärtuse faktorid õppijate edu mõjutavad. Kursusele registreerumise motivatsiooni faktoritest mõjutab selle uurimuse põhjal õppijate edu lähtudes nende kavatsusest kursuse suhtes kursusel saadava tunnistuse kasulikkus. Varasemate uurimuste põhjal mõjutavad kursuse lõpetamisest lähtuvat edu huvi kursuse vastu, õppijate sobivus veebipõhiseks õppeks, sotsiaalsed mõjud ning sobivus töö ja pereeluga. Nii selle kui varasemate uurimuse tulemused on näidanud, et kursuse lõpetamist mõjutab õppijate ajakasutus.

Mudeli kolmas osa annab ülevaate faktoritest, mis on mõjutatud ootustest ja väärtustest. Doktoritöö ja teaduskirjanduses leiduva põhjal mõjutavad kursuse lõpetamist valikud, mida õppijad teevad seoses kursuste tegevustega ning õppijate sooritus kursusel. Kaasatuse faktoritest mõjutab õppijate edu lähtudes õppijate

kavatsustest õppematerjalide sees olevate väliste materjalidele viivate linkide külastamine. Varasemad uurimused on leidnud, et kursuse lõpetamist mõjutavad foorumi ja lugemismaterjalide kasutamine ning õppevideote mitmekordne vaatamine.

Doktoritöö tulemused on kasulikud, et mõista erinevaid õppijate edu lähene-misi ja edu mõjutavaid tegureid MOOCidel. See uurimus laiendab õppijate edu käsitlust teaduskirjanduses, eriti õppijate kavatsustel põhinevat edu. Tulemused võivad olla kasulikud MOOCide korraldajatele, et mõista paremini kursusel osa-lejate käitumist ja toetusvajadust nende edu taustal ning anda sisendit selleks, et MOOCe kuluefektiivsemaks muuta.

PUBLICATIONS

CURRICULUM VITAE

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Education

2020–(2024) University of Tartu, PhD studies in Computer Science
2019 –2020 University of Tartu, PhD studies in Computer Science (extern)
2015–2017 University of Tartu, Master’s degree (MA), Educational Management, *cum laude*
2007–2009 University of Tartu, Master’s degree (MSc), Teacher of Mathematics
2007–2009 University of Tartu, Master’s degree (MSc), Teacher of Informatics
2004–2007 University of Tartu, Bachelor’s degree (BSc), Information Technology (Software)
2001–2004 Nõo High School
1992–2001 Riidaja Secondary School

Employment

2019–... Playtech Estonia, Senior Deployment Manager
2015–2019 Playtech Estonia, Deployment Manager
2011–2015 Playtech Estonia, Quality Assurance Engineer
2007–2011 Playtech Estonia, Client Tester

Scientific work

Main fields of interest:

- Use of computers in learning and teaching mathematics
- Informatics didactics

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Haridus

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2019 –2020	Tartu Ülikool, PhD, informaatika (ekstern)
2015–2017	Tartu Ülikool, sotsiaalteaduse magister (MA), hariduskorraldus, <i>cum laude</i>
2007–2009	Tartu Ülikool, loodusteaduse magister (MSc), matemaatikaõpetaja
2007–2009	Tartu Ülikool, loodusteaduse magister (MSc), informaatikaõpetaja
2004–2007	Tartu Ülikool, tehnikateaduse bakalaureus (BSc), infotehnoloogia
2001–2004	Nõo Reaalgümnaasium
1992–2001	Riidaja Põhikool

Teenistuskäik

2019–...	Playtech Estonia, tarkvara uuenduste vanemhaldur
2015–2019	Playtech Estonia, tarkvara uuenduste haldur
2011–2015	Playtech Estonia, kvaliteedi tagamise insener
2007–2011	Playtech Estonia, kliendi testija

Teadustegevus

Peamised uurimisvaldkonnad:

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